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Decision Support for Reducing 30-Day Readmissions: General Medicine Patients in Community Hospitals

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DECISION SUPPORT FOR REDUCING 30-DAY READMISSIONS: GENERAL MEDICINE PATIENTS IN COMMUNITY HOSPITALS

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To my beloved grandfather and loving family

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ABSTRACT

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Health expenditures in United States have experienced a gradual increase in spending with no indication of slowing down. Addressing this problem has been a major area of concern for policy makers, and as a result more consideration has been placed on decreasing health spending and increasing affordability. One major area recognized as being effective in decreasing these financial burdens has been inpatient thirty-day adult readmissions, currently costing $26 billion annually. Centers for Medicare & Medicaid Services (CMS) have determined readmissions to be an indicator of the quality and efficiency of patient care.

This research provides a prediction model for patients at ‘high-risk’ of 30-day readmissions patients in rural and urban hospital settings. These results are integrated into a decision support tool that combines the mathematical design, published discharge interventions, and financial model for use by hospital administrators. This tool was created to give ‘control’ back to hospital managers and improve the decision making process in reducing hospital readmission rates. Through this work we show the mathematical model, intervention process work flow, and decision support tool.

CHAPTER 1. INTRODUCTION

1.1 Status of United States Healthcare

Health expenditure in the United States is constantly rising, with the most recent estimate in 2011 nearing $2.7 trillion [1]. The United States healthcare system, as in any other country, mirrors the country's economic prosperity. However studies have shown that the United States spends significantly more on healthcare than any other industrialized country, with current estimates surpassing $8,500 per capita in health costs [2]. Countries such as Switzerland and Norway spend nearly two-thirds as much, while others including Japan and New Zealand only spend one-third [3, 4]. The sufficiently higher average per capita costs is related to a rise in total expenditure on health care as a percentage of GDP from 1980, with the most recent estimate around 17.7% in 2011 [5]. In contrast to other developed countries a greater proportion of health care spending in the United States is financed by private insurance and 'out-of-pocket' payments, and as a result less than half (47.8%) of spending is publicly funded [4, 6]. In addition, it has been noted that the prices of procedures, prescription drugs, and office visits in the United States are the highest of any other country [6]. Hospital care and physician/clinical services currently account for over half of the nation's health expenditure [7, 8].

1.2 Reducing Costs and Improving Quality

These higher costs do not appear to stem from a better quality of care as would be expected and desired. Quality indicators such as; five-year survival rates for different cancers, preventable mortality rates, and in-hospital fatality are not performing at a justifiably high level, relative to other counties [4, 6, 9]. Therefore this has been a major area of concern for policy makers, resulting in attempts to mitigate unnecessary health spending and increase affordability. The introduction of the Affordable Care Act (ACA) in 2010 [10, 11] was aimed at resolving these issues by expanding both public and private insurance coverage. This was done to decrease the uninsured rate and reduce healthcare costs for patients and the government. In order to accomplish these goals the act created a set of mechanisms which included subsidies, mandates, penalties, and insurance exchanges to increase coverage [12]. As a result, it appears that reducing spending while increasing the quality of care is a pressing concern and requires changes to be made in the delivery, insurance coverage, and reimbursement polices within healthcare. Several avenues have been discussed in this area and the focus surrounding thirty-day readmissions has gained a strong foothold and support.

1.3 In-patient Readmission

Readmissions are defined as an admission to a hospital within thirty days of discharge from either the same or another hospital. As of fiscal year (FY) 2013, readmissions were measured by any in-patient admission over the age of 18, who was not considered a ‘planned’ rehospitalization. Only patients who were scheduled for the following two procedures were categorized as ‘planned’ readmissions; heart attack patients who later underwent coronary artery bypass graft surgery and percutaneous coronary intervention [13]. Several facets of the healthcare structure can be improved, and the impact from a reduction in hospital readmissions of in-patient adults is no exception. The thirty-day readmission rate is attracting attention from several institutions and payers including; the Institute of Medicine, Centers for Medicare & Medicaid Services (CMS), and the Medicare Payment Advisory Commission as an indicator of the quality and efficiency of patient care [14, 15], Readmissions are a significant contributor to healthcare costs with nearly one fifth of Medicare beneficiaries [16] discharged from acute care hospitals readmitted in 30 days, costing $26 billion annually [1]. In response, with authorization from the ACA of 2010, CMS penalized hospitals for 30 day readmissions of Medicare and Medicaid patients after October 1, 2012 [10, 11]. Therefore the predictive modeling of patients' readmission probability has been sought after by clinicians, hospital administrators, and ward staff.

1.4 Discharge Intervention Programs & Financial Impact

Along with the growing interest in accurately predicting patients at 'high-risk' of readmission, several discharge intervention programs have been developed. Each one possesses a bundle of steps that have been proven as a whole to have a positive impact on readmission rates. Certain intervention packages have been tailored to better assist clinicians throughout the discharge process [17-20]. Current practice calls for various intervention bundles targeted at post-discharge support [21], front-loaded home care [22], remote monitoring [23], and self-management [24]. Therefore, as soon as a particular patient has been identified as 'high risk', a particular intervention or set of interventions are conducted in order to assist in reducing the patient's chance of being hospitalized again.

As with the introduction of any additive measure to improve quality of patient care there is an associated financial implication. Under controlled conditions the estimated intervention cost per patient has been noted to range from $100 [24] to $424 [25]. Managers must assess who is responsible for carrying out the indicated intervention steps, the time dedicated to each action, as well as proper resource allocation for satisfactory results. With several published intervention packages this becomes burdensome on hospital administrators and identifying the most appropriate route with which to proceed appears convoluted.

1.5 Decision Support

In order to allow for informed choices to be made by decision makers (hospital administrators, clinicians, etc.) several questions must be asked and appropriate information must be provided. To be able to make smarter decisions administrators need to begin by asking the following questions:

1. What should the target reduction in readmission rates be?
2. Which discharge intervention packages/bundles should be implemented?
3. Who accomplishes which tasks and what are the appropriate resources for allocation?
4. Which ('high-risk') patients are to receive a particular intervention?
5. How will this impact readmission rates and what are the financial implications?

In order to achieve this, several models are needed and should be integrated in a user-friendly software package. Therefore we set out to develop a mathematical model that accurately predicts thirty-day in-patient readmission probabilities, a financial model that incorporates a variety of costs for tailored discharge interventions, and an operationalized intervention work flow model utilizing published literature. These models were created and integrated into a package called the *Readmission Simulator*, under a grant funded by the Indiana Hospital Association through the Partnerships for Patient Initiative.

1.6 Research Contributions

The readmission model and decision support tool presented here are new additions to the field of healthcare operation research and are extremely valuable in the area of intervention planning for reducing hospital readmissions. Although work has been done in the area of readmission prediction and discharge planning, new research has not previously incorporated the aforementioned approach while providing health administrators with the power to make smarter choices. The contributions of our research are as follows:

1. Establishment of a mathematical model in predicting thirty-day readmission rates for general in-patients in community hospitals;
2. Utilization of imputation techniques for missing data to improve prediction of ‘high-risk’ patients;
3. Development of a financial model to predict intervention impact on hospital inpatient revenue;

4. Creation of intervention work flow processes in the areas of comprehensive discharge planning, disease self-management, and medication self-management;
5. Development of a prototype decision support tool which integrates these research results into an user friendly software for hospital administrators.

1.7 Thesis Organization

This thesis is organized into the following chapters. Chapter 2 reviews literature on identifying ‘high-risk’ patients, discharge interventions, and the associated financial factors. Chapter 3 describes the problem in detail. Chapter 4 explains the mathematical model and provides the methodology behind predicting thirty-day readmissions. Chapter 5 explains the decision support tool and impacts for health administrators. Chapter 6 summarizes the results, lists areas for future work, and indicates limitations to the current research.

CHAPTER 2. LITERATURE REVIEW

2.1 Government Action in United States Healthcare

With the establishment of the Affordable Care Act (ACA) the current focus in medicine has been shifted to controlling financial costs while improving the overall quality of care. To assist in this process the *Readmissions Reduction Program* (by CMS) was established as a way to encourage hospitals to decrease the number of annual readmissions seen nationwide. Since this effort improves the quality of care and decreases costs, those hospitals failing to improve their readmission rates receive penalties. As stated by CMS, "Section 3025 of the Affordable Care Act added section 1886(q) to the Social Security Act establishing the Hospital Readmissions Reduction Program, which requires CMS to reduce payments to IPPS hospitals with excess readmissions, effective for discharges beginning on October 1, 2012 [11, 13]." In FY 2013 those hospital's with readmission rates in excess of the national averages for Acute Myocardial Infarction (AMI), Heart Failure (HF) and Pneumonia (PN) began receiving penalties up to 1% of CMS reimbursement. Subsequently in FY 2014 the readmission adjustment factor rises to 2%. Furthermore, CMS is expanding penalized conditions, bringing the total to five conditions, FY 2015 to include patients admitted for an acute exacerbation of chronic obstructive pulmonary disease (COPD) and patients admitted for elective total hip arthroplasty (THA) and total knee arthroplasty (TKA). Current discussions surrounding the readmission adjustment factor appears to be trending towards a 3% maximum penalty by FY 2015 [11, 13].

2.2 Identifying High Risk Patients

Due to the financial implications and expansion of penalties, the predictive modeling of patients' readmission probability has been sought after by clinicians, hospital administrators, and ward staff. The ability to identify 'high risk' patients within the first 24 hours of admission would allow the hospital staff to proactively intervene in the discharge process by tailoring proven interventions on a case by case manner. Researchers have identified patient characteristics associated with thirty-day readmissions [26], and several prediction models have been published. However a model focused on general in-patients admitted to community hospitals has not previously been developed. Investigators have either considered a specific in-patient population [27-31], examined a limited hospital situate (e.g. one hospital, teaching hospital, Veteran Affairs (VA) hospital) [32-35], or a single disease/condition [36-39].

These developed models are classified into the following categories: models relying on retrospective administrative data [27, 40-52], utilizing real-time administrative data [28, 53, 54], incorporating retrospective primary data collection [34, 55-60], or exploiting real-time primary data [30, 61-65]. Of the fourteen studies covering retrospective administrative data, ten were based on United States healthcare data. Out of those, five concentrated on Medicare inpatients [46, 47], two on congestive heart failure (CHF) patients [43, 44], two on inpatients 65 years and older [45, 48], and one on a single VA hospital [27]. The motivation behind such models is that high-risk patients can be easily identified facilitating prompt delivery of targeted intervention programs. Out of the three studies focused on real-time administrative data, one was completed in England [53], while the other two models received data from a single United States hospital focused only on CHF patients [28] or patients eligible for mandatory Medicaid managed care enrollment [54].

Considering the models using retrospective primary data collection, three were limited to patients greater than 65 years old [55, 56, 58] and observed a utilization outcome of thirty-day, 180-day, and 1-year readmissions respectively. Of these model types one of them was conducted in a single rural hospital in Ireland [56]. Another study conducted 90-day readmission analysis on patients 45 years and older [34], while two others focused on 90-day readmissions for all medical inpatients at a single county hospital [59, 60]. A model constructed through the same data collection method was created and validated for thirty-day readmission prediction using a Canadian data set [57].

Out of the six investigations using primary data collected in real time, three used a *Probability of Repeated Admission* (PRA) instrument which Boult et al. initially developed to predict repeat admissions over a 4 year time span [30, 62, 63]. Two were conducted with data from patients admitted to a single VA hospital [64, 65]. The final model of this group was produced by Hasan et al. and considered all age thirty-day readmissions in general medicine patients admitted to several academic centers [61].

However, these models have not considered cases in which certain patient factors may not have been collected resulting in missing data fields. Typically instances which involved these occurrences are eliminated during the data exclusion phase of research and data cleaning. Although one would like to consider cases in which all the patient characteristics have been collected upon admission this is not always realistic in the real world. Therefore our research considers a set of models; a general all age in-patient design, a model based on hospital situate, and an imputation design for missing patient data.

Now having a better idea of how this thesis fits into the established literature we dedicate the following sections for papers that relate to our work. Section 2.3 discusses the developed prediction models relying on retrospective administrative data. Section 2.4 examines models that were created by utilizing real-time administrative data. Section 2.5 explores models constructed by retrospective primary data. Section 2.6 reviews models constructed by real-time primary data. Sections 2.7 through 2.12 reviews discharge interventions aimed at reducing readmissions, and conclude by deliberating on intervention procedures and associated finances.

2.3 Models Relying on Retrospective Administrative Data

Several papers have previously investigated the readmission prediction problem through the use of retrospective administrative data. For our problem we will consider only those cases conducted in the United States as the differences in healthcare systems are quite large. However, we note that the approach for development of such models can be considered for future designs of experiments. Krumholz et al. created several mathematical models in a joint effort with CMS to predict readmission rates for AMI, Pneumonia, and CHF, respectively. Each model was based on one years' worth of data from the United States general population on Medicare patients older than 65. They used a hierarchical logistic regression model with inpatient and outpatient claims data from the

12 months prior to admission for model deviation and validation with the evaluated outcome being all-cause readmission for the aforementioned disease/conditions. This model considered and excluded 'planned' readmission from the final discharge data set as well as those patients that die within thirty days of a discharge. The end result was a model that included a large administrative data set of AMI, CHF, and pneumonia patients for a modest area under the receiver operating characteristic (ROC) of 0.63, 0.60, and 0.63 respectively. The investigators ultimately found prior hospitalization, treatment in a tertiary care hospital, higher comorbidity score, male gender, and prolonged length of stay during admission to be important predictors in these patients [50-52].

Hammill et al. [43] and Philbin & DiSalvo [44] also considered a model that was condition specific, in this case it was only CHF patients. However, Philbin and DiSalvo contributed the notion of using United States data from multiple centers across a single state to create a more targeted model. Although the researchers used data obtained within a calendar year they aimed to predict thirty-day readmission. The approach required statistical analyses of a chi-square table and Student unpaired *t* test with the final model being a logistic regression type. They discovered that individuals of the African American race, Medicare and Medicaid insurance, prior cardiac surgery, and those whom historically had certain conditions/diseases (peripheral vascular disease, idiopathic cardiomyopathy, diabetes mellitus, ischemic heart disease, anemia, and renal disease) tended to have a greater risk of readmission. The end result was a modest model that produced a ROC score of 0.60 [44].

A few additional models considered utilization outcomes other than thirty-day readmission including; 60-day readmissions in Anderson & Steinberg [47], 60-day mortality and readmissions by Naessens et al. [48], and 15-, 30-, 60-, and 90-day readmissions based on diagnosis from Thomas [46]. While Holloway et al, considered medical, neurologic, and geriatric inpatients admitted to a single Veteran Affairs (VA) hospital over a one year period, although they did not indicate the model discrimination level through a c-statistic [27].

Silverstein et al. provided an interesting model founded on thirty-day readmission in patients greater than or equal to 65 years using data over two years at seven acute care hospitals from the Dallas-Fort Worth area. For this model the researchers split the analytical patient sample into a two-thirds deviation and one-thirds validation cohort and then analyzed significant variables by a logistic regression design, retaining variables significant at the $p < 0.05$ level. Age greater than 75 years, male gender, African American race, health system variables (long-term care, insurance status, and surgery service), and a range of different comorbidity variables were found to be significant in predicting readmissions. Therefore the final model was deemed to have a modest discrimination with a c-statistic of 0.65 [45].

2.4 Models Using Administrative Data in Real Time

Further readmission prediction models were developed with the underlying administrative data collected in real time. Amarasingham et al. presented a model focused on CHF patients over a one year period from a single United States center to predict thirty-day readmissions. The developed model was established on a multivariate linear regression framework using data extracted from electronic medical records (EMR), resulting in what these investigators considered significant predictors for their ‘electronic readmissions model'. Those included mortality risk factor (Tabak mortality score), depression or anxiety history, demographic factors, health behaviors, number of prior inpatient admissions, and time of emergency department (ED) arrival. This model produced an overall c-statistic of 0.72 with no evidence of a lack of fit ($p > 0.85$). The key contribution from this work is that when incorporating complex social factors the model's accuracy increases substantially signifying that these particular factors could further strengthen readmission prediction [28]. In addition, automating this process through electronic means would allow for the timely identification of 'high-risk' patients while still hospitalized providing clinicians with valuable information.

Billings and Mijanovich approached this problem with a similar 'real-time' goal in order to develop effective intervention strategies for patients at high-risk for readmission. Claims records, over a four year timeframe, for Medicaid fee-for-service disabled adult patients (eligible for Medicaid managed care) were used. A logistic regression model was developed and then a split sample of half the appropriate population was assigned to the model set while the remaining half comprised the validation set. The target utilization outcome was a 12-month readmission. Besides that, the authors contributed a business-case model which their algorithm used to assess the financial impact of interventions on targeted patients. Cases for different patient risk levels were considered and assumed interventions were analyzed, providing the foundation of an integrated prediction and financial model [54].

2.5 Models Relying on Retrospective Primary Data

In a series of investigations Smith et al. collected data on medical inpatients from a single United States county hospital to observe 90-day readmissions rates. By conducting a multivariate analysis of fourteen patient characteristics, found at the time of discharge, five were determined to be significant in readmission prediction with a c-score of 0.66. Those individuals with higher serum urea nitrogen levels, PO_2 <80 mmHg, white blood cell count ≥12,000, more frequent emergency room (ER) visits in the past 6 months, and anemia tend to be at a higher readmission risk. In presenting the idea of using patient and clinical data found at the time of discharge, Smith et al. established the foundation for using retrospective primary data for these prediction methods as early as 1985 [34, 59, 60].

Krumholz et al. took a similar approach to assign a group of high-risk patients by using patient and clinical factors for predicting readmissions within 6 months. This study was limited to patients at least 65 years old with a principle discharge diagnosis of CHF in across several Connecticut hospitals. From a multivariate analysis four factors were determined to be significant including; prior heart failure, diabetes, creatinine level > 2.5 mg/dL at discharge, and admissions within the past year. However in this study no c-statistic was reported for model discrimination. This combination of clinical and patient factors was proven to deliver strong predictability for all-cause readmissions as well as heart-failure readmissions. [58]

Other investigators in this field have advanced this issue of predicting ‘high-risk’ patients by utilizing retrospective primary data, although not necessarily for readmission cases. Eric Coleman, considered by many to be the founder of care transition interventions, used this approach to predict thirty-day 'complicated care transitions' as defined by; transfers from lower-to higher-intensity care environments without prior relapse. The study used Medicare Current Beneficiary Survey Cost and Use (MCBS) files and corresponding Medicare claims data. Although Coleman et al. did not predict readmission probabilities they pointed out an important observation, showing that the combination of administrative and self-reported data compared to administrative data alone increased the ROC *c*-score (0.833 vs. 0.771) [55]. This study highlighted the importance of the care transitions process and active assessment of risk during a hospital stay.

2.6 Models Relying on Real Time Primary Data

The most clinically relevant models that provide readmission prediction in real time involve the use of primary data. First off, this data can be collected within the hospital during the patients' stay and, as seen in models relying on real time administrative data; this has a vast impact on patients, providers, and insurance. Second, using primary data provides accurate up-to the minute information that will be quickly obtained upon admission. Hasan et al. provided the most useful and pertinent model. These investigators used data typically determined within the first 24 hours of an admission. In addition, they developed a model focused on general medicine patients ages 18 and older while aiming to establish a simple predictive model. Through analyzing medical records and making post-discharge telephone follow-up calls, patients' factors were categorized and placed under a logistic regression analysis. In addition, this study conducted a Medical Outcomes Study Short Form 12 (SF-12) questionnaire. The authors produced a model validated for seven significant predictive factors; insurance status, marital status, having a regular physician, Charlson comorbidity index, SF-12 physical component score, ≥1 admission within the last year, and current length of stay >2 days. This resulted in a fair model with a *c*-statistics of 0.65 and 0.61 for the derivation and validation cohorts respectively [61]. This model by Hasan et al. added to this area of research by creating a general model without an age or disease/condition restriction and demonstrated the usefulness of approaching this problem in such manner. However, this model used data collected from an academic center and may not be as relevant to patients attending community hospitals, due to a variety of procedural differences. This appears to be an important area to consider in developing a predictive model moving forward.

A few other investigators resorted to observing only medical inpatients older than 65 and provided similar results as previously seen. Burns & Nichols investigated patients admitted to a single VA for 60-day readmissions, however failed to produce model discrimination characteristics. Although this was the case they were able to use a logistic regression model to determine that chronically ill patients and those who had several admissions in the past year tended to be readmitted most frequently [64]. Several models used the *Probability of Repeated Admission* (PRA) instrument which Boult et al. initially developed to predict repeat admissions over a 4 year time span. This tool was developed to be a questionnaire to assess and score the eight factors identified to be seen in repeat admissions in the elderly. Older age, male sex, poor self-rated general health, availability of an informal caregiver, coronary artery disease, hospital admission and more than six doctor visits within the previous year, and diabetes were information collected in the tool following the determination of factor significance in repeat admissions [30, 62, 63]. The significant contribution of these studies however was the PRA instrument as a means to manually identify ‘high-risk’ patients by completing a simple scoring checklist.

2.7 Discharge Interventions

As health service researchers begin identifying patient characteristics associated with thirty-day readmissions, a variety of discharge interventions have been published and shown to reduce that risk. Individuals argue that identifying these ‘high-risk’ patients is the first step of discharge planning around proven interventions. Overall, the published literature has focused on two key areas in reducing readmissions; improved hospital discharge processes as well as strengthened post-discharge support. Essentially, these interventions place emphasis on improved patient education and self-management, a multi-disciplinary team management, and enhanced discharge & transitional care [66]. According to Boutwell et al., these classifications have brought about a wide range of interventions including those; identifying patients at high risk of post-discharge problems [67], discharge planning protocols [68], pre- & post-discharge home visits [69, 70], daily discharge rounds [71], post-discharge support programs [21, 72], improved patient and family education [24, 73], telephone follow-up after discharge [74], transitional units [75], enhanced communication between hospital and primary care providers [76], clinical nurse specialists [77], liaison nurses and discharge coordinators [78], intensive in-hospital discharge preparation [79], and some other standalone studies [80-83].

Given the wide range of interventions available we chose to look more closely at investigations that appeared clinically relevant, indicated significant reduction in readmissions, were reproducible, and contained/conducted financial cost benefit analysis. We analyzed those investigations dealing with post-discharge support [21], front-loaded home care [22], remote monitoring [23], self-management [24], and a few published bundle packages [17, 19, 84].

2.8 Post-Discharge Support

Phillips et al did a meta-analysis over a set of studies that described the effects of discharge interventions in patients admitted for CHF. The investigators offered a discharge plan with post-discharge support based on their analysis. In the meta-analysis, they included only randomized controlled clinical trials. These studies however varied in the intensity and duration of counseling administered by the discharging center (from 1 to 3.5 hours per patient), frequency, and manner in which patients were followed up. Certain interventions included a single home visit, scheduled clinic follow-up, phone calls, extended home care services, and hospital day services. During these post-discharge support sessions several different aspects of patient care were addressed including; medication review/counseling, daily weight measurements/monitoring, enforcing dietary and fluid restrictions/counseling, social service consultation, and exercise training. The follow-up duration of these different support mechanisms were 3-, 6-, 9-, or 12-months.

For articles containing a single home visit, an 11-16% absolute risk reduction was observed, while scheduled clinic follow-up articles resulted in a 12% decrease of absolute risk. Home visits of different frequencies range from 4-23% reduction in risk and day hospital services observed a 25% reduction in absolute risk. Extended home care services showed a 6-13% risk reduction.

As discharge support encompasses a wide range of intervention possibilities, which are capable of changing, it became difficult to assess expected clinical readmission reduction. However, in the aforementioned meta-analysis it was observed that these trials culminated in a 25% relative reduction in readmission risk in CHF patients which indicates a significant change. The reported average cost for conducting these interventions in the United States was approximately $81 monthly per patient. However, the drawback of this support structure is the lack of standardization with operational roles and safe-guards for unforeseen circumstances [21].

2.9 Front Loaded Home Care

Stewart et al. conducted a home-based intervention on chronic CHF patients discharged following an acute care admission. This intervention was conducted through the help of a multi-disciplinary team in which patients were randomly assigned to receive a home visit, between 7-14 days of discharge. Patients were counseled about their prescription regimen, encouraged to weigh themselves daily and told to monitor fluid intake. For some patients (38% of cases), following the index home visit the cardiac nurse was required to contact the patients' primary care physicians to conduct a review of clinical status and prescribed medications. This intervention encompassed 6 months of follow-up care and witnessed a 40% reduction in readmission. However this may be an inflated number due to the few patients in the study (77 in intervention group). Nonetheless, this intervention structure observed a decrease in the number of readmissions and fewer associated hospital days. The mean cost for the studied intervention was $228 per discharged patient [22].

2.10 Remote Monitoring

In a systematic review of studies focused on telemonitoring of CHF patients, Chaudhry et al. observed promising results for the improvement of disease management and readmission reduction. Telemonitoring is gaining attention from clinicians as a viable option utilizing various communication avenues to monitor patients' clinical status. Excitement has been mounting as the possibility to collect clinical data without requiring face-to-face visits provides numerous possibilities and drastically expands healthcare accessibility. There were three types of remote monitoring techniques used in the reviewed articles; telephone-based symptom monitoring, automated monitoring of signs and symptoms, and automated physiologic monitoring.

Initial models of symptom monitoring were conducted by nurses through one-on-one phone call with the patients. However individuals responsible for initiating management changes and the hierarchical structure of information flow/response differed based on intervention complexity and patient populations. Overall studies were designed with some underlying similarities to ensure adherence by collecting data pertinent to; daily physical activity, symptom monitoring, fluid intake status, medication regime, and diet. Investigations based on symptom tracking were accomplished by uploading information into an electronic communication device. The collected data was monitored and reviewed by nurses and physicians who resulted in decisions to be offered up by the health care team. Investigations utilizing automated physiologic monitoring system to reduce readmissions produced positive results. In the article discussed, the authors placed systems into the patients' residence that allowed for daily self-monitoring of; heart rate, blood pressure, oxygen saturation, and weight. Comparing readmission results to home visit data showed an 40% reduction in heart failure readmissions at less than half the cost ($2.87 daily). Although this was one study, automated physiologic monitoring appeared to be cost-effective.

2.11 Self-Management

Previous studies revealed the need to improve patient education at the time of discharge was clearly important. Koelling et al. observed that combining patient education and post-discharge support had an effect on reducing readmissions, however the benefits attributed to patient education separately had yet to be determined. Therefore, they set out to determine this correlation by testing its impact on clinical outcomes in CHF patients. In a randomized controlled study, they compared the effects of a one hour face-to-face teaching session with a trained nurse to standard discharge protocol at the time of discharge, in heart failure patients. The entirety of the intervention was done within the hospital at time of discharge. The patient education session included discussions of basic CHF principles, dietary restriction rationale, and daily self-care engagements (weight monitoring, action items for worsening symptoms, smoking and alcohol cessation, etc.). At the end of study an analysis demonstrated that those exposed to the one hour patient centered education observed a relative readmission reduction of 35%, at only an additional $100 per patient. This demonstrated a significant reduction in rehospitalizations and is a testament to the importance of spending quality time on properly educating patients upon discharge [24].

2.12 Bundled Intervention Programs

As a result of the widely recognized success in the areas of post-discharge support, front-loaded home care, remote monitoring, and self-management in reducing readmissions several researchers began developing bundled interventions. These different programs utilized aspects of the aforementioned areas to develop a ‘redesigned’ discharge process aimed at reducing readmissions and the associated risk. Williams et al. focused on this approach and produced a highly regarded program called Project BOOST (Better Outcomes for Older adults Through Safe Transitions) in order to optimize the hospital discharge process. This intervention embraced the movement towards a ‘patient-centered care’ model allowing patients to partake in a more engaging role in personal care and decision making. To accomplish this, the intervention incorporated nurse-patient teach back mechanisms, providing outpatient providers with timely discharge records, and scheduling an outpatient follow-up appointment or phone call within 72 hours [19]. Installing this program resulted in reducing readmission within hospitals across the United States, albeit with varied degrees of success.

Jack et al. developed a similar intervention strategy targeted towards minimizing hospital usage following discharge. This study, later became known as Project RED (Reengineered Hospital Discharge), comprised of multiple facets with components during hospitalization and post-discharge. There were three main intervention components; a discharge advocate, after-hospital care plan, and a pharmacist led post-discharge telephone conversation. The in-hospital component included patient's education on diagnosis, arranging clinician follow-up appointments, organizing post-discharge services, medication reconciliation and assessing patient understanding of the process. The estimated cost per patient for Project RED participants was $122 [85]. The result seen in Project RED was a decrease in hospital utilization among general medicine patients within thirty days of discharge by 30% [18]. Therefore these researchers claimed that proper discharge planning focused on the patient not only at the time of discharge but also afterwards would significantly reduce the risk of rehospitalization. These intervention bundles greatly improve the quality of patient care, provide a positive financial impact for both hospitals and Medicare, and allocate resources in a systematic fashion once 'high-risk' patients have been identified.

CHAPTER 3. PROBLEM STATEMENT

3.1 Predictive Model for Decision Support

Apparent from literature, readmission prediction models in the past have focused on disease/condition, payor type, and/or age while limited to academic/teaching hospitals. In addition researchers are seen using different data types for unique analysis; either from a retrospective or primary analysis. However, a general model focused on all admitted in-patients from multiple community hospital sites has not yet been developed. A design established in retrospective primary data can develop a baseline for a real-time model providing the greatest flexibility and reliable predictive power.

Creating this type of model would be extremely beneficial for healthcare administrators by providing an early means to predict readmissions among all admitted patients. We set out to develop a predictive model using patient data obtainable within the first 48 hours of admissions. To do such predictive work we decided to use data from community hospitals across the state of Indiana to better determine risk in real-time. The results from a mathematical model based on this premise would allow for appropriate patient treatment and timely administration of discharge interventions.

3.2 Decision Support

This approach would produce the foundation for the development of an integrated decision support software established across electronic medical record data identifying high-risk patients in a precise and opportune manner. Therefore, we sought to develop a simulation tool which allowed end users to compute readmission probabilities retrospectively as well as in real-time through an innovative solution. We positioned ourselves to combine mathematical modeling with an interactive user interface. This approach would allow us to create a software package which identifies high-risk patients in an accurate and pertinent manner. In order to accomplish this, a two-faceted model was designed for users to upload real hospital discharge data into a template. In turn this model which would internally compute readmission probabilities, among other factors, and display results in a graphical interface. The underlying motivation for this tool was to allow hospitals to take control of their own data and be able to easily run some predictive analytics on real clinical admissions. Both population as well as individual patient readmission prediction can be computed in the tool, as the user desires, in addition to simulating different published discharge interventions for cost/benefit analyses.

3.3 Intervention Integration

However, there is an issue with these published discharge intervention bundles. Researchers have yet been able to identify which actions (steps) are attributed to the reduction in readmission rates. In essence, resources may not be properly utilized and the allocation of personnel in certain functions is not adequately defined. These progressions, in which functions are completed, appear in cases to be up to user interpretation which may be the cause of varying results. Due to the vast number of unique clinics nationwide, an operationalized intervention discharge process aimed at reducing hospitalizations, educating patients, and utilizing resources in a systematic manner must be set. In order to create a model following these parameters, each step in the process must be separately tested to determine the impact on readmission risk and the associated costs while defining responsible healthcare providers.

From the literature, it is observed that several investigators tested similar parts of the discharge process and found significant overlaying concepts. Such concepts surrounded comprehensive discharge planning, medication self-management, and disease self-management. Therefore we set out to operationalize these significant procedures and develop three unique work-flow maps all targeted at a common goal of reducing readmission (Figures 3.1-3.5). In order to ensure that interventions produce reliable, relatable, and repeatable results across different locations these maps provide a process foundation. Once implemented, reduction of readmission associated to an intervention can be calculated and the expected financial implications estimated.

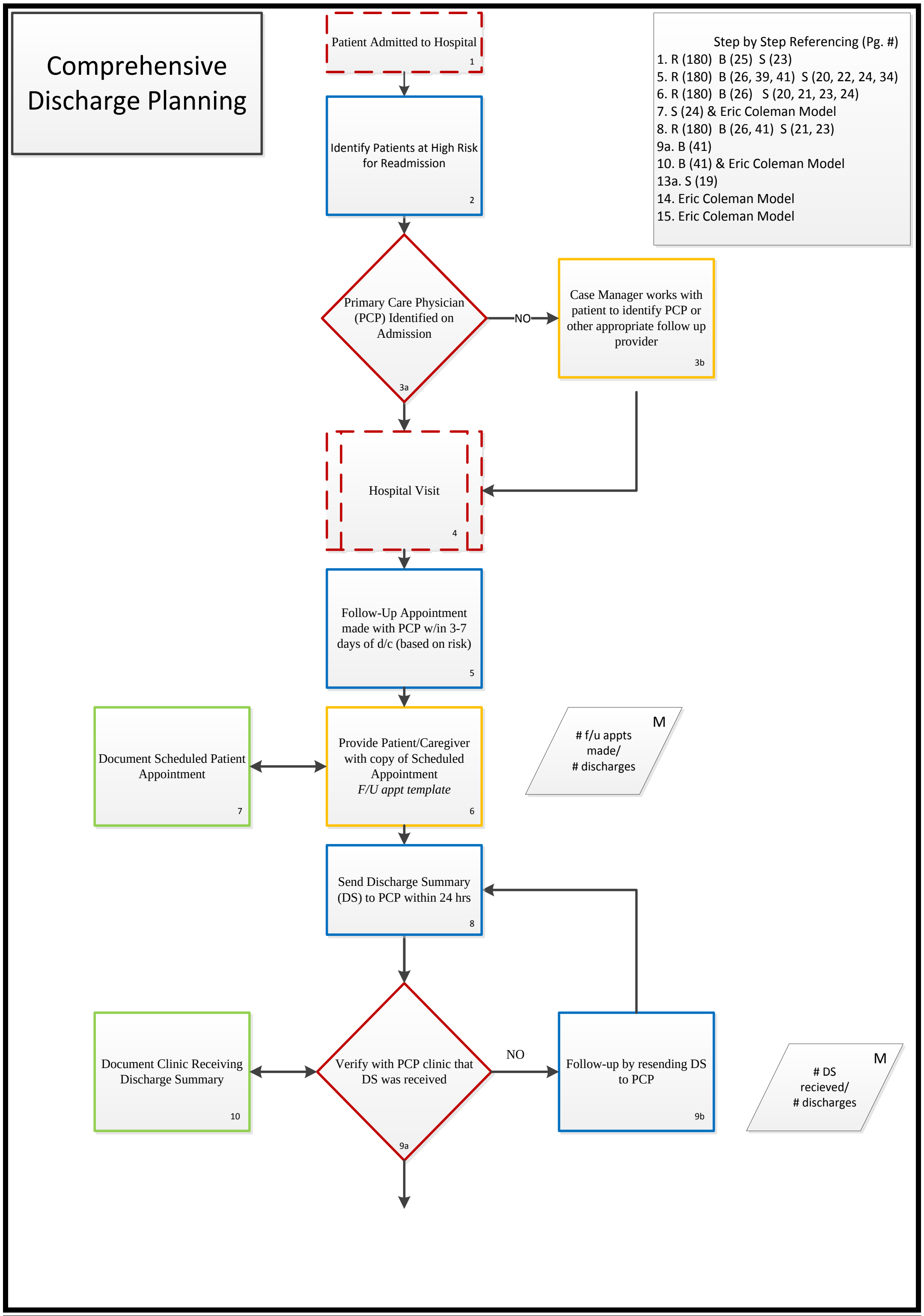

Figure 3.1 Comprehensive Discharge Planning Intervention Process Flow (1/2)

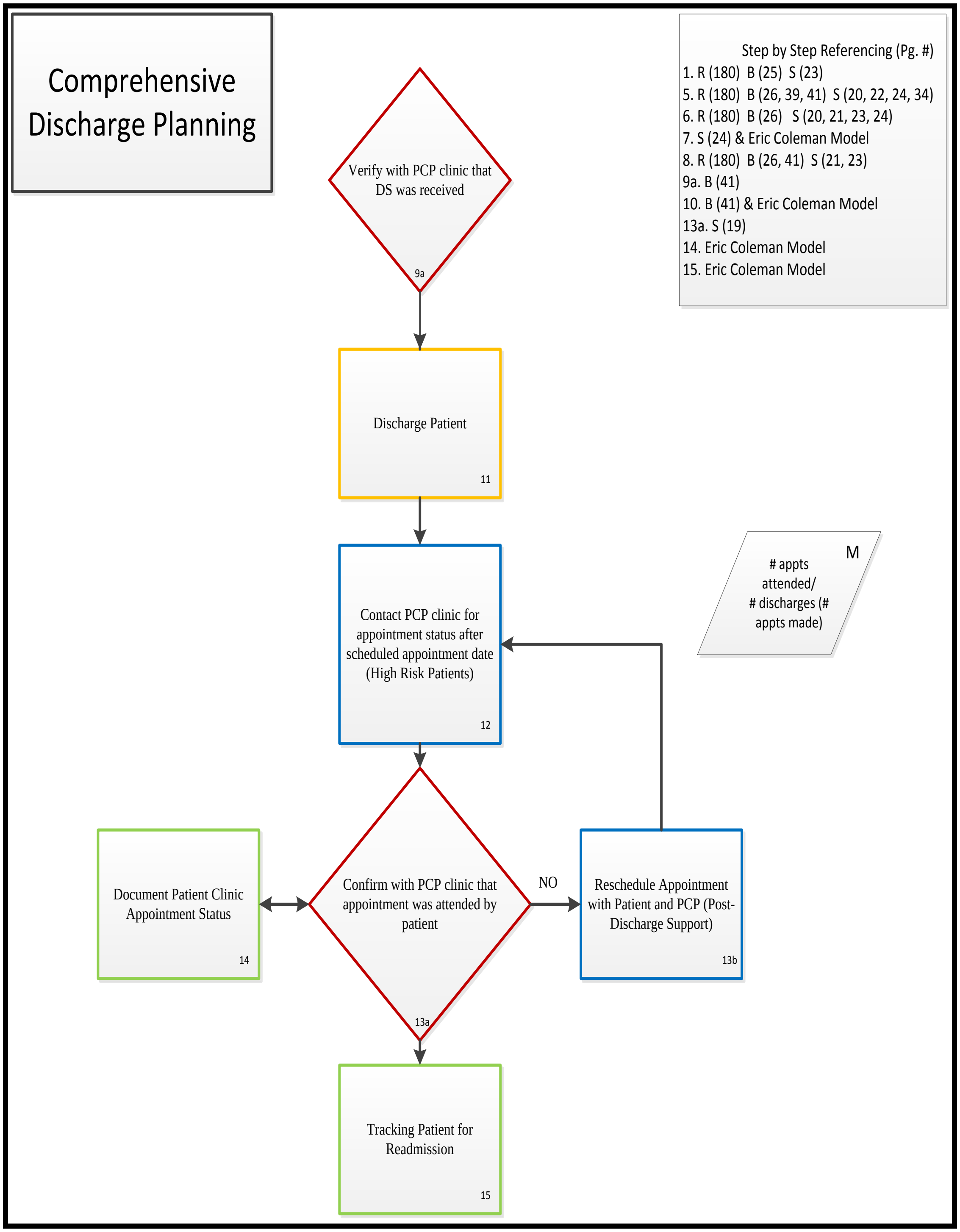

Figure 3.2 Comprehensive Discharge Planning Intervention Process Flow (2/2)

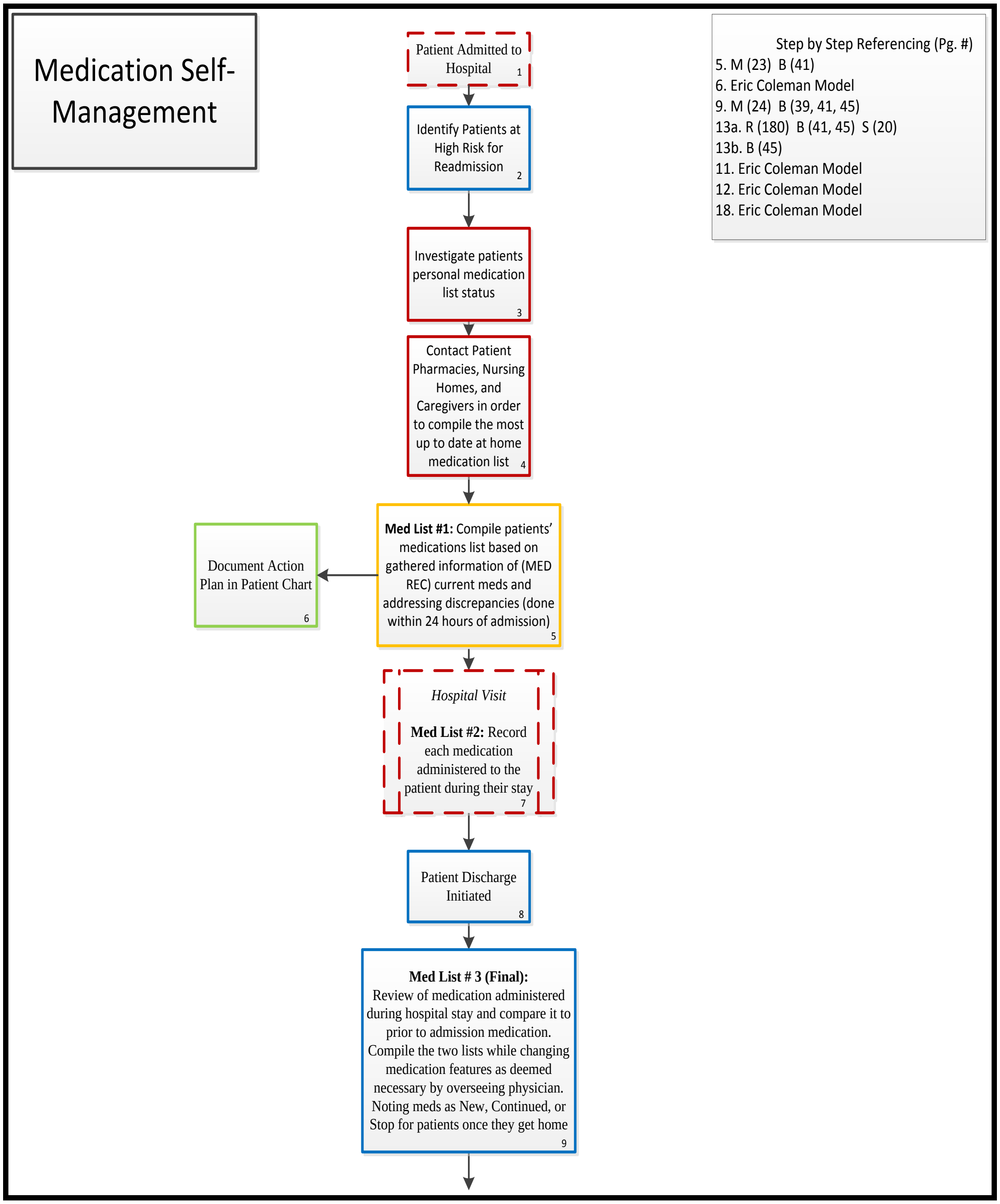

Figure 3.3 Medication Self-Management Intervention Process Flow (1/2)

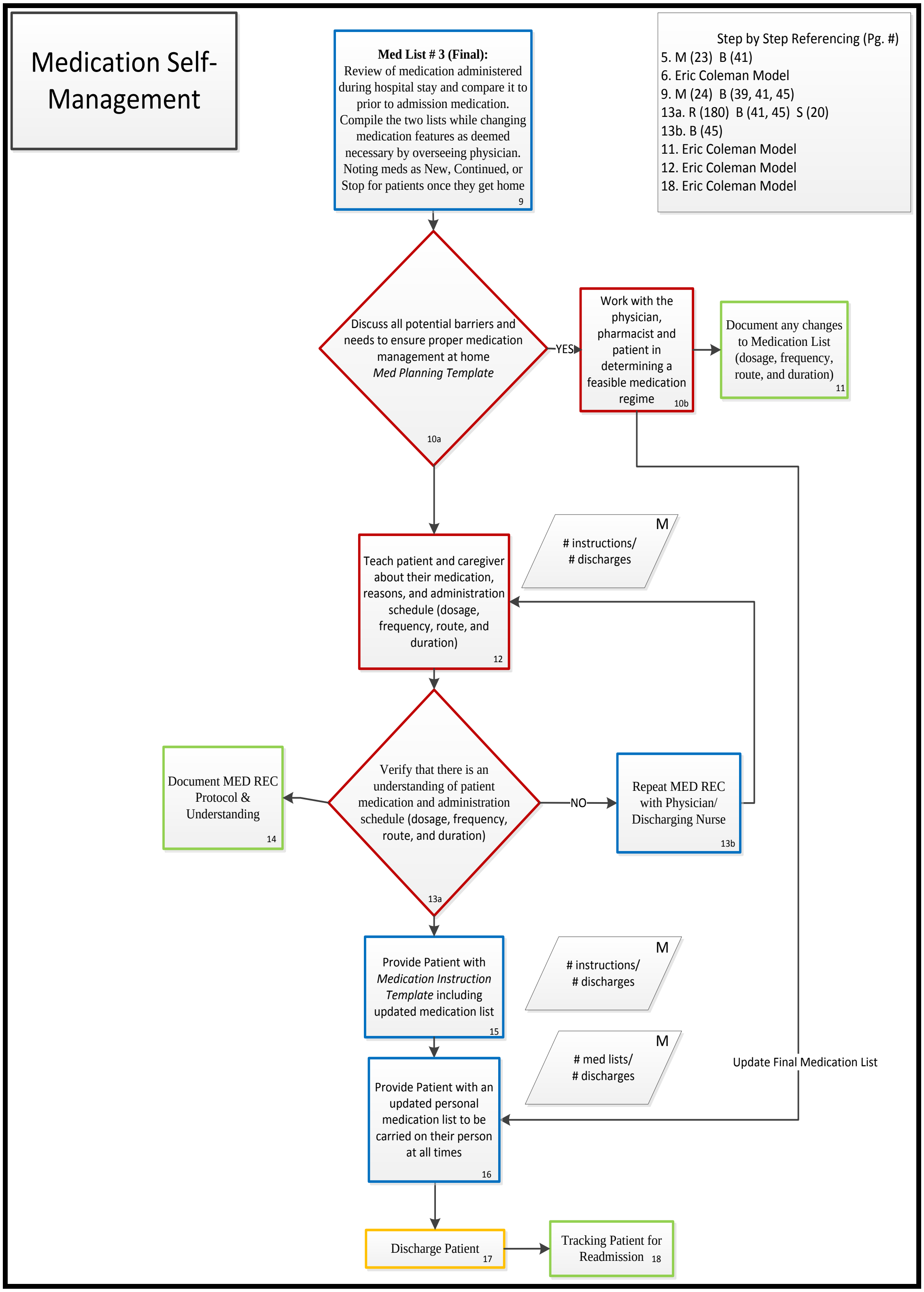

Figure 3.4 Medication Self-Management Intervention Process Flow (2/2)

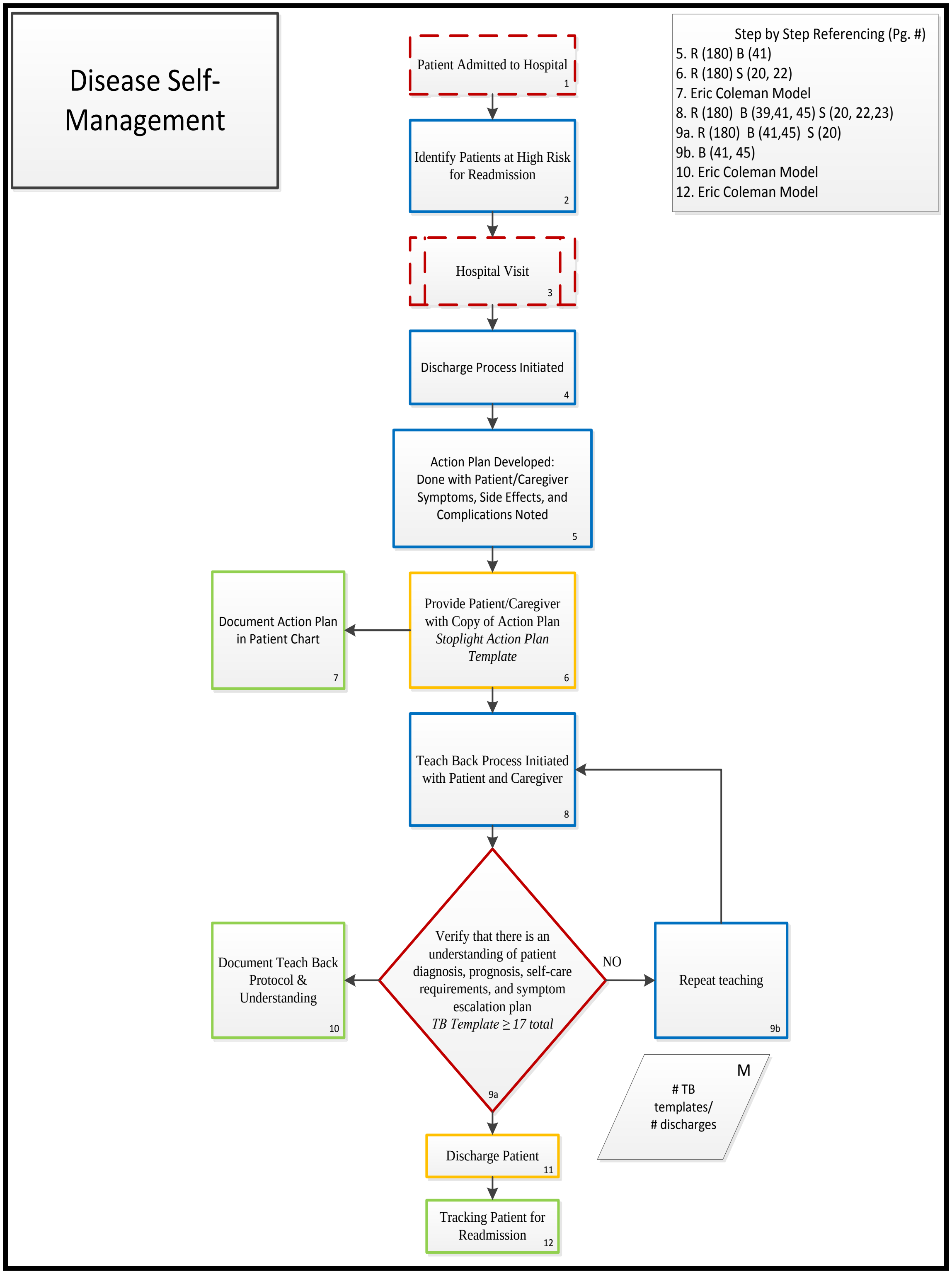

Figure 3.5 Disease Self-Management Intervention Process Flow

CHAPTER 4. THIRTY-DAY READMISSION PREDICTION

4.1 Methods

4.1.1 Study Population

This study was conducted with patient discharge data from three community hospitals, across Indiana, admitted as general medicine in-patients. Patients aged 18 years and older who were admitted between December 2008 and September 2012 at two rural hospitals and one urban hospital were included in the study. Patients who died in hospital during the primary admission were removed from analysis.

4.1.2 Data Characteristics

The patient characteristics that were incorporated in the model were found in the following four categories; social support, health condition, socio-demographic, and healthcare utilization. Patient records were de-identified and included insurance status, marital status, identified primary care provider, age, admission/discharge dates, ICD-9 codes, and diagnosis related group (DRG). Additional data fields were collected from the urban hospital including; admission source, discharge disposition, and gender. Several models were developed, to capture the unique characteristics of each data set. An aggregated (general) model that incorporated all patient data provided by the partnering hospitals, rural, urban, expanded urban and imputed model were created using data (sub) sets representative of each model design (Figure 4.1).

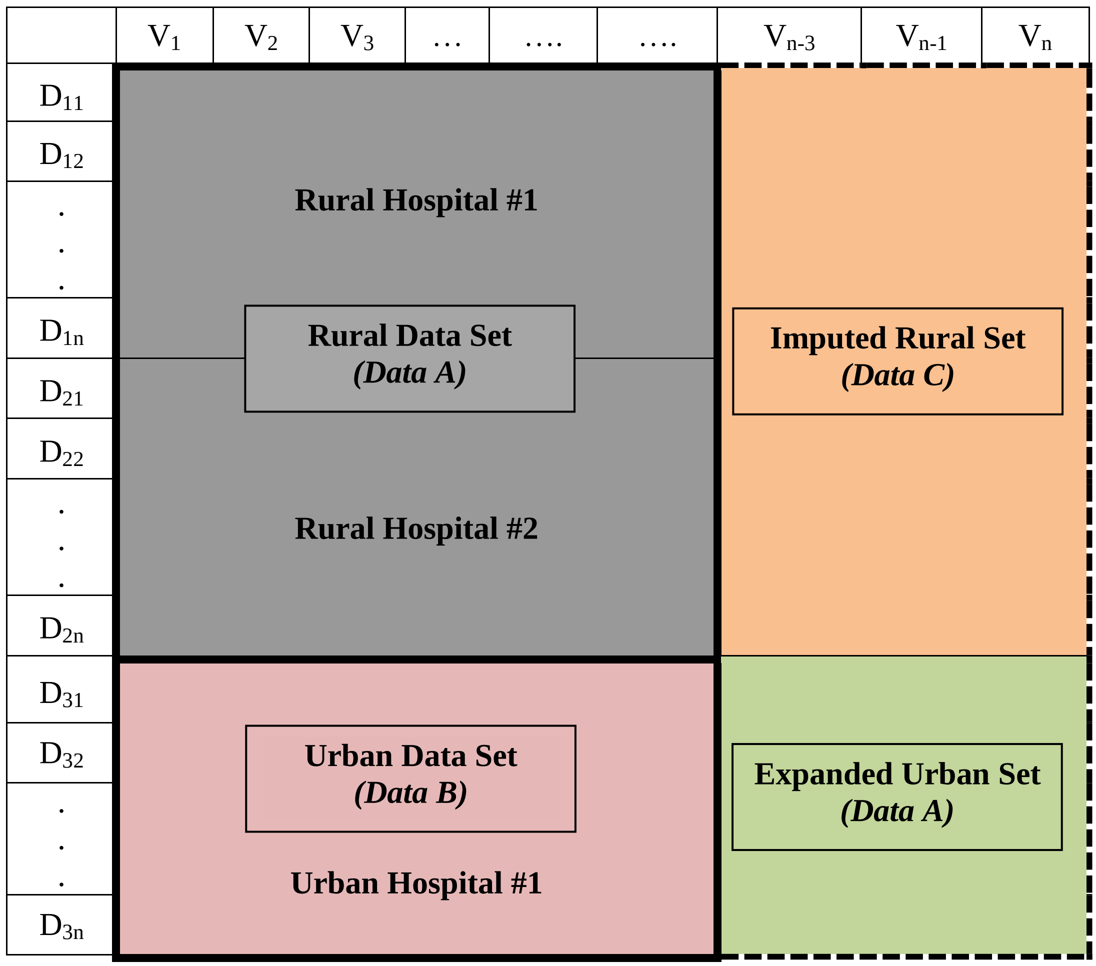

Figure 4.1 Visual Data Description

Table 4.1 Model Design By Utilized Data Set

	Data Set			
Model Design	**A**	**B**	**C**	**D**
General	✓	✓		
Rural	✓			
Urban		✓		
Expanded Urban		✓		✓
Imputed	✓	✓	✓	✓

4.1.3 Exclusion Criteria

In the general model discharges with improper data fields (i.e. payor type, marital status, admit/discharge date) and below the age of 18 were removed from the analyses as not to skew the final results (Figure 4.2). Of the patients included in the general model, 12.3% (n=5,075) of discharges were excluded. Overall, 21,127 patients (pts.) accounting for 36,234 discharges (d/c) were included. The urban expanded model removed patients who were not admitted from the emergency department (ED), a non-acute healthcare facility, or an ambulatory center. Likewise discharges of patients to dispositions other than their home, assisted living or long-term care, and acute or sub-acute rehabilitation facilities were excluded (Figure 4.3). In the urban model 5.1% (n=919) of d/c and 3.5% (n=429) of pts. were excluded as failing to contain the appropriate admission source, discharge disposition, and/or gender criteria. In turn, the urban model comprised data from 17,098 d/c and 11,804 pts. The rural model on the other hand contained 19,136 d/c for 9,323 pts.

The study was approved by each site's institutional review board, which included exemption from requiring written informed consent because our study involved the examination of medical record data and posed no risk to enrolled patients. No patients were contacted during the course of this study.

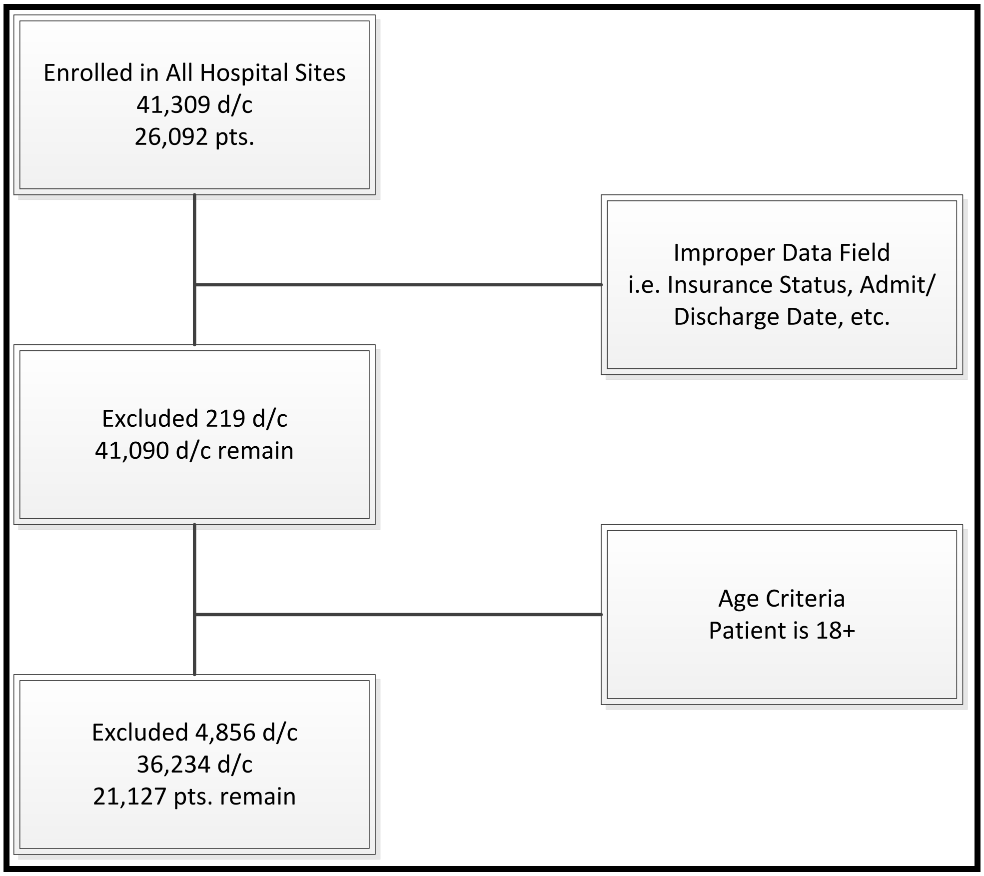

Figure 4.2 All Hospital Data Exclusion Criteria

Figure 4.3 Urban Hospital Data Exclusion Criteria

4.1.4 Statistical Analysis

Given the large number of discharges we chose to make patient discharges the unit of analysis; with a split-sample design to derive and internally validate our prediction model. For the general community hospital model, we randomly selected two thirds of discharges from each site to create a derivation cohort and the remaining one third of discharges was set to establish a validation cohort. The rural and urban models derived both the model and validation sets utilizing the same methodology. The expanded urban and imputed model encompassed additional patient factors including; admission source, discharge disposition, and gender that were otherwise excluded from the general, rural, and urban models. A published study [85] assessed that a grouping of patients by age was a particular area of interest in developing a more specific and accurate readmission risk. Therefore, each model design categorized patients by two age ranges (1)18-64 and (2) 65+, in which individuals within the age ranges were separated and analyzed following an aggregated all patient model was established. We fixed separate multivariable logistic regression models to the patient factors using data from the derivation cohort in order to assess whether the proposed characteristics were significantly associated with hospital readmission. We used a p-value < 0.05 as the cutoff for assessing significance. Only factors noted to be significantly associated with readmission were included in the final regression model.

We tested the performance of our model using data from the validation cohort. The models goodness of fit was evaluated using the Hosmer–Lemeshow chi-square test [86], model discrimination by measuring the area under the receiver operating characteristic (ROC) curve [87], and log-likelihood. Since older patients as well as those discharged to long or short-term care facilities are an important patient population and may have different predictors of readmission, we repeated our procedure for these particular populations in the extended urban and imputed analysis. For our purposes we refer to the model encompassing data from all hospital sites as the general model, and the prediction model with only urban hospital data as the urban model, likewise for the rural model. The model referred to as the imputed model with all characteristics seen in the expanded urban model, contains imputed data across all missing fields in the rural patients (Table 4.1). All analyses were performed using SAS statistical software (Version 9.3; SAS Inc. Cary NC) and R 2.15.1.

4.1.5 General Model Design

This particular model contained aggregated patient data across three Indiana community hospitals ranging in size and location. The general model contains three unique parts; an all age patient model and two models based on an age factor (either 18-64 or 65+). This model established baseline comparisons for the subsequently produced rural and urban models. The descriptive statistics of the aggregated hospital patient discharge data (Entire Cohort) can be seen in Table 4.2. The same approach was taken for both the urban and rural models, using the same patient data characteristics separated based on hospital location.

4.1.6 Expanded Model Design

This model was developed to produce a comparison between the general in-patients setting to the expanded model with subsequent data inclusion. This was also compared to the imputed model. The expanded urban model contained the data observed in the general urban model and the aforementioned additional factors seen in Table 4.3. This model is presented in an all age and age group comparison as done for the general models. For the imputed model the same characteristics seen in the expanded urban model are used with the goal to ‘impute’ the non-provided data fields for the rural hospitals. The motivation behind such an approach was to determine the usefulness of replacing missing data with a suitable value as was not collected in the case of the rural hospitals and observe the impact on model improvement. In order to view additional imputation effects on full model design a subset of patient characteristic were randomly removed and imputed for each case to be analyzed.

Table 4.2a Patient Characteristics Entire Data Set by Location

	Entire Cohort n= 36,234		Urban Cohort n= 17,098		Rural Cohort n= 19,136	
Characteristic	**n**	**(%)**	**n**	**(%)**	**n**	**(%)**
Readmitted	5,354	14.78%	1,424	8.33%	3,930	20.54%
Age group						
≤40 years	7,626	21.05%	5,034	29.44%	2,592	13.55%
41–50 years	2,781	7.68%	1,471	8.60%	1,310	6.85%
51–60 years	4,031	11.12%	2,068	12.09%	1,963	10.26%
61-70 years	5,002	13.80%	2,519	14.73%	2,483	12.98%
≥71 years	16,629	45.89%	6,006	35.13%	10,623	55.51%
Age group by RA						
≤40 years	591	11.04%	200	14.04%	391	9.95%
41–50 years	382	7.13%	127	8.92%	255	6.49%
51–60 years	557	10.40%	165	11.59%	392	9.97%
61-70 years	696	13.00%	234	16.43%	462	11.76%
≥71 years	3,048	56.93%	698	49.02%	2,350	59.80%
Primary Insurance						
Medicare	22,810	62.95%	8,255	48.28%	14,555	76.06%
Medicaid	3,831	10.57%	1,590	9.30%	2,241	11.71%
Self-pay	2,935	8.10%	1,002	5.86%	1,933	10.10%
Private	6,657	18.37%	6,251	36.56%	406	2.12%
Primary Insurance by RA						
Medicare	4,166	77.81%	925	64.96%	3,241	82.47%
Medicaid	429	8.01%	66	4.63%	363	9.24%
Self-pay	344	6.43%	73	5.13%	271	6.90%
Private	415	7.75%	360	25.28%	55	1.40%
Marital Status						
Currently Married	16,774	46.29%	9,314	54.47%	7,460	38.98%
Not Currently Married	19,460	53.71%	7,784	45.53%	11,676	61.02%

Table 4.2b Cont. Patient Characteristics Entire Data Set by Location

	Entire Cohort n= 36,234		Urban Cohort n= 17,098		Rural Cohort n= 19,136	
Characteristic	**n**	**(%)**	**n**	**(%)**	**n**	**(%)**
Marital Status by RA						
Currently Married	2,143	40.03%	698	49.02%	1,445	36.77%
Not Currently Married	3,211	59.97%	726	50.98%	2,485	63.23%
Regular Physician						
Yes	22,550	62.23%	10,560	61.76%	11,990	62.66%
No	13,684	37.77%	5,114	29.91%	8,570	44.78%
Regular Physician by RA						
Yes	3,634	67.87%	1,202	84.41%	2,432	61.88%
No	1,720	32.13%	222	15.59%	1,498	38.12%
Admissions in Last Year						
0 to 1	30,281	83.57%	15,431	90.25%	14,850	77.60%
2 to 3	4,176	11.53%	366	2.14%	3,810	19.91%
4+	1,776	4.90%	1,301	7.61%	475	2.48%
Admissions in Last Year by RA						
0 to 1	3,267	61.02%	1,092	76.69%	2,175	55.34%
2 to 3	1,272	23.76%	112	7.87%	1,160	29.52%
4+	815	15.22%	220	15.45%	595	15.14%
Current Length of Stay						
1–2 days	4,827	13.32%	2,132	12.47%	2,695	14.08%
> 2 days	31,407	86.68%	14,966	87.53%	16,441	85.92%
Current Length of Stay by RA						
1–2 days	554	10.35%	161	11.31%	393	10.00%
> 2 days	4,800	89.65%	1,263	88.69%	3,537	90.00%

Table 4.3 Patient Characteristics for the Urban Expanded Cohort

	Urban Expanded Cohort n= 17,098	
Characteristic	**n**	**(%)**
Readmitted	1,424	8.33%
Admission Source		
Emergency Department	8,932	52.24%
Non-acute Healthcare Facility or Ambulatory	8,166	47.76%
Admission Source by RA		
Emergency Department	824	57.87%
Non-acute Healthcare Facility or Ambulatory	600	42.13%
Discharge Disposition Criteria		
Home	13,423	78.51%
Assisted living or Long-term Care	3,031	17.73%
Acute or Sub-acute Rehabilitation Facility	644	3.77%
Discharge Disposition Criteria by RA		
Home	886	62.22%
Assisted living or Long-term Care	462	32.44%
Acute or Sub-acute Rehabilitation Facility	76	5.34%
Gender		
Male	5,791	33.87%
Female	11,307	66.13%
Gender by RA		
Male	601	42.21%
Female	823	57.79%

4.2 Results

4.2.1 General Model

The outcome variable of all cause 30 day readmission was computed retrospectively by observing any admission detected following the indexed admission within 30 days, and represent 14.78% of all discharges in the population. Across the hospital sites the readmission rates to these specific hospital sites within thirty-days ranged from 8.3-21.7%, resulting in 5,354 discharges being classified as a readmit and with 802 patients being readmitted multiple times (≥2). From the four classifications of patient factors there were six significant predictors of 30 day readmission identified in the general model (Table 4.4); insurance status, marital status, having a primary care physician, Charlson Comorbidity Index [88, 89], number of admissions within the last year, and current length of stay (>2 days). The Hosmer-Lemeshow goodness of fit (HLGOF) test yielded a p-value of 0.1333, which indicates a strong model fit [90]. Discrimination of the model was modest: the area under the ROC curve (AUC) was 0.71 in the derivation cohort and 0.70 in the validation cohort. We then segregated the data based on age group ranges and found that for those who are 18-64 years old, length of stay was not significant, while for patients 65 and older the comorbidity index was not a significant predictor of thirty-day readmission. With the non-significant factors removed from the initial age group models and re-analyzed, all remaining patient characteristics were found to be significant predictors. When the HLGOF test was performed on the age group models, p-values of 0.0918 and 0.2518 were found for each group respectively. Discrimination of the subsequently produced age grouped models (Table 4.5) was modest for the younger classification with AUC values of 0.73 and 0.72 in the deviation and validation cohorts, while the older age set produced AUC values, of a fair model, 0.65 in both cohorts.

Table 4.4 All Sites General Model for All Patients

All Sites General Model			
	All Patients *(n=36,234)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	*P* value
Insurance			
Medicare	*0.4587*	*2.534 (2.206-2.911)*	*<.0001*
Medicaid	-0.0658	1.500 (1.245-1.807)	0.2334
Self-pay	0.0782	1.732 (1.426-2.104)	0.1838
Private	Reference		
Currently Married	*-0.0828*	*1.180 (1.092-1.275)*	*<.0001*
Have a regular physician	*0.0566*	*0.893 (0.823-0.968)*	*0.0062*
Charlson index	*0.0919*	*0.832 (0.769-0.900)*	*<.0001*
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.1797*	*3.186 (2.902-3.497)*	*<.0001*
≥ 4	*0.7993*	*5.919 (5.220-6.712)*	*<.0001*
Current length of stay >2 days	*0.155*	*0.733 (0.651-0.827)*	*<.0001*

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.5 All Sites General Model by Patient Age

	All Sites General Model					
	18-64 Age Group *(n=16,637)*			65+ Age Group *(n=19,597)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	*P* value	Beta Coefficient	Odds Ratio (95% CI)	*P* value
Insurance						
Medicare	*0.3452*	*1.907 (1.572-2.313)*	*<.0001*	*-0.3352*	*1.069 (0.722-1.581)*	*0.0077*
Medicaid	-0.0634	1.267 (1.029-1.562)	0.0286	0.1279	1.698 (0.865-3.333)	0.5858
Self-pay	0.0185	1.376 (1.105-1.712)	0.7727	*0.6089*	*2.747 (1.226-6.156)*	*0.0321*
Private	Reference			Reference		
Currently Married	*-0.1372*	*1.316 (1.139-1.519)*	*0.0002*	*-0.0679*	*1.146 (1.043-1.258)*	*0.0044*
Have a regular physician	*0.2563*	*0.599 (0.524-0.684)*	*<.0001*	*-0.0662*	*1.141 (1.030-1.266)*	*0.012*
Charlson index	*0.2498*	*0.607 (0.526-0.700)*	*<.0001*	***	***	***
Admissions in last 1 year						
0 to 1	Reference			Reference		
2 to 3	0.0543	2.939 (2.482-3.481)	0.3677	*0.1846*	*3.248 (2.900-3.637)*	*<.0001*
≥ 4	*0.9696*	*7.341 (6.049-8.909)*	*<.0001*	*0.8088*	*6.063 (5.149-7.140)*	*<.0001*
Current length of stay >2 days	***	***	***	*-0.2304*	*0.631 (0.538-0.739)*	*<.0001*

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

4.2.2 Rural Model

For the all age patient model (Table 4.6) in the rural setting all indicated significant factors from the all age general model remained significant. This produced an AUC c-score of 0.69 for the model with a 0.065 HLGOF value. However for the younger age group (18-64), marital status was found to not be significant and removed from the final regression structure. This younger age group model had an AUC c-score of 0.72 while the HLGOF produced a p-value of 0.4784. The older group required even more variables to be removed including; insurance type, marital status, and primary care physician visits. With the removal of these factors the resulting final model contained a fair AUC value of 0.68 and an HLGOF value of 0.2871 (Table 4.7).

4.2.3 Urban Model

Comparing to the all ages general model, factors such as marital status, comorbidity index, and length of stay were not significant in the urban model. However, removing such factors and establishing a succeeding model the HLGOF test produced a poor p-value <0.0001 and modest AUC values of 0.76 and 0.73 respectively (Table 4.8). Albeit the urban model for all ages required some patient factors to be removed we investigated its impact on age groups as was previously done for the general model, using its framework as the starting point. Insurance and marital statuses were non-significant factors for the age group 18-64, and removed from the model; resulting in a HLGOF test p-value of 0.052 and modest AUC values of 0.76 and 0.74 (Table 4.9). On the other hand for the older age group, a few additional factors were required to be removed; primary care physician, and comorbidity. This caused a HLGOF test p-value of 0.5746 and modest AUC values of 0.69 and 0.70 in deviation and validation cohorts respectively.

Table 4.6 Rural Model for All Patients

	Rural Model		
	All Patients *(n=19,136)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance			
Medicare	*0.3687*	*2.017 (1.047-3.888)*	*<.0001*
Medicaid	-0.0104	1.381 (0.704-2.707)	0.9204
Self-pay	-0.0254	1.360 (0.691-2.678)	0.8139
Private	Reference		
Currently Married	*0.0571*	*1.121 (1.017-1.236)*	*0.0219*
Have a regular physician	*-0.0575*	*0.891 (0.809-0.983)*	*0.0209*
Charlson index	*0.0813*	*1.177 (1.068-1.297)*	*0.0010*
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.2335*	*3.365 (3.006-3.767)*	*<.0001*
≥ 4	*0.7465*	*5.621 (4.878-6.477)*	*<.0001*
Current length of stay >2 days	*-0.2620*	*0.592 (0.505-0.695)*	*<.0001*

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.7 Rural Model by Patient Age

	Rural Model					
	18-64 Age Group *(n=16,637)*			65+ Age Group *(n=19,597)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	*P* value	Beta Coefficient	Odds Ratio (95% CI)	*P* value
Insurance						
Medicare	*0.4523*	*2.855 (1.298-6.279)*	*<.0001*	***	***	***
Medicaid	0.0779	1.964 (0.885-4.356)	0.5138	***	***	***
Self-pay	0.0667	1.942 (0.873-4.321)	0.5856	***	***	***
Private	Reference			Reference		
Currently Married	***	***	***	***	***	***
Have a regular physician	*-0.1968*	*0.675 (0.569-0.800)*	*<.0001*	***	***	***
Charlson index	*-0.1514*	*0.739 (0.609-0.896)*	*0.0021*	*0.1697*	*1.404 (1.250-1.577)*	*<.0001*
Admissions in last 1 year						
0 to 1	Reference			Reference		
2 to 3	*0.2076*	*3.369 (2.742-4.140)*	*0.0033*	*0.2445*	*3.357 (2.927-3.851)*	*<.0001*
≥ 4	*0.7995*	*6.090 (4.839-7.664)*	*<.0001*	*0.7222*	*5.413 (4.500-6.511)*	*<.0001*
Current length of stay >2 days	*-0.3006*	*0.548 (0.424-0.708)*	*<.0001*	*-0.2456*	*0.612 (0.497-0.754)*	*<.0001*

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.8 Urban Model for All Patients

	Urban Model		
	All Patients *(n=17,098)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance			
Medicare	*0.2759*	*1.381 (1.162-1.641)*	*0.0001*
Medicaid	*-0.4132*	*0.693 (0.489-0.982)*	*0.0016*
Self-pay	0.1842	1.260 (0.892-1.779)	0.1555
Private	Reference		
Currently Married	***	***	***
Have a regular physician	*0.2397*	*0.619 (0.508-0.755)*	*<.0001*
Charlson index	***	***	***
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.5498*	*8.535 (7.212-10.102)*	*<.0001*
≥ 4	*1.0446*	*14.000 (10.735-18.257)*	*<.0001*
Current length of stay >2 days	***	***	***

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.9 Urban Model by Patient Age

	Urban Model					
	18-64 Age Group *(n=9,490)*			65+ Age Group *(n=19,597)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance						
Medicare	***	***	***	***	***	***
Medicaid	***	***	***	***	***	***
Self-pay	***	***	***	***	***	***
Private	Reference			Reference		
Currently Married	***	***	***	***	***	***
Have a regular physician	*0.2424*	*0.616 (0.474-0.800)*	*0.0003*	***	***	***
Charlson index	*0.7181*	*0.238 (0.099-0.569)*	*0.0013*	***	***	***
Admissions in last 1 year						
0 to 1	Reference			Reference		
2 to 3	*0.64*	*13.450 (10.139-17.843)*	*<.0001*	*0.4885*	*6.599 (5.375-8.100)*	*<.0001*
≥ 4	*1.3191*	*26.526 (17.016-41.352)*	*<.0001*	*0.9098*	*10.055 (7.243-13.959)*	*<.0001*
Current length of stay >2 days	*0.115*	*1.556 (1.125-2.151)*	*0.0075*	-0.145	0.748 (0.558-1.004)	0.0532

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

4.2.4 Expanded Urban Model

The urban model analyses was expanded in order to understand the impact that these additional factors had on predicting readmissions; admission source, discharge dispositions, and gender. The all age expanded urban model initially contained the entire set of observed predictors and then required the exclusion of marital status, comorbidity index, and length of stay along with two of the additional factors; admission source and gender. Eradicating this factors and creating a consequent model with the HLGOF test a p-value of 0.0029 and modest AUC values of 0.77 and 0.76 were found respectively (Table 4.10). As for the younger age group, insurance and marital statuses, gender, and admission source were not found significant; resulting in a model that the HLGOF test had a p-value of 0.0321 with modest AUC values of 0.77 and 0.75 (Table 4.11). The older age group found insurance and marital statuses, comorbidity index, length of stay, gender, and admission source as not significant patient factors; consequently constructing a model with a HLGOF test p-value of 0.0771 and modest AUC values of 0.73 for both cohorts (Table 4.12).

4.2.5 Imputed Model

For this model type designed with all age patient data from the expanded urban set and imputed rural set all variables except admission source was found significant. This resulted in more variables found in the final imputed model than in the urban expanded model. In turn the all patient age model generated a p-value of 0.0494 for the HLGOF test and modest AUC values of 0.72 (Table 4.13). Likewise similar analysis was done for the younger group given this data set and found that all variables were significant in the final model. The 18-64 age group model contained a modest AUC with a c-score of 0.75 and a p-value of 0.0046 from the HLGOF test (Table 4.14). On the other hand several factors had to be excluded from the older age group model as insurance, marital status, primary care physician visits, and Charlson Index were not found as significant (Table 4.15). Therefore this model generated a p-value of 0.5594 for the HLGOF test and a fair AUC value of 0.68. For the experimental analysis on generated missing data sets c-scores ranged from 0.65 & 0.73 for the cases of simulating the removal of half the number of admissions in the last year and the Charlson Index values respectively (Table 4.16). The HLGOF test scores produced p-values between 0.0039 & 0.5468 for the case of simulating the removal of half the number of admissions in the last year and the marital status respectively.

Table 4.10 Expanded Urban Model for All Patients

Urban Expanded Model			
	All Patients *(n=17,098)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance			
Medicare	0.1109	1.104 (0.917-1.328)	0.1462
Medicaid	*-0.3805*	*0.675 (0.475-0.959)*	*0.0038*
Self-pay	*0.2575*	*1.278 (0.904-1.806)*	*0.0483*
Private	Reference		
Currently Married	***	***	***
Have a regular physician	*0.2425*	*0.616 (0.505-0.751)*	*<.0001*
Charlson index	***	***	***
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.5457*	*8.419 (7.105-9.976)*	*<.0001*
≥ 4	*1.039*	*13.788 (10.545-18.029)*	*<.0001*
Current length of stay >2 days	***	***	***
Admission Sources			
E.D.	***	***	***
Non-acute Healthcare Facility or Ambulatory	Reference		
Discharge Disposition			
Home	*-0.4002*	*0.570 (0.408-0.797)*	*<.0001*
Assisted Living or Long-term Care	*0.2379*	*1.079 (0.759-1.532)*	*0.0015*
Acute or Sub-acute Rehabilitation Facilities	Reference		
Patient Gender Male	***	***	***

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.11 Expanded Urban Model for Younger Patients

Urban Expanded Model			
	18-64 Age Group *(n=9,490)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance			
Medicare	***	***	***
Medicaid	***	***	***
Self-pay	***	***	***
Private	Reference		
Currently Married	***	***	***
Have a regular physician	*0.221*	*0.643 (0.494-0.836)*	*<.0001*
Charlson index	*0.741*	*0.227 (0.095-0.541)*	*0.0008*
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.6482*	*12.961 (9.751-17.228)*	*<.0001*
≥ 4	*1.2656*	*24.034 (15.304-37.743)*	*<.0001*
Current length of stay >2 days	*0.2223*	*1.560 (1.121-2.172)*	*0.0084*
Admission Sources			
E.D.	***	***	***
Non-acute Healthcare Facility or Ambulatory	Reference		
Discharge Disposition			
Home	*-0.4467*	*0.558 (0.319-0.977)*	*0.0002*
Assisted Living or Long-term Care	0.3104	1.190 (0.611-2.319)	0.0527
Acute or Sub-acute Rehabilitation Facilities	Reference		
Patient Gender Male	***	***	***

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.12 Expanded Urban Model for Older Patients

Urban Expanded Model			
	65+ Age Group *(n=7,608)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance			
Medicare	***	***	***
Medicaid	***	***	***
Self-pay	***	***	***
Private	Reference		
Currently Married	***	***	***
Have a regular physician	*0.1775*	*0.701 (0.516-0.953)*	*0.0234*
Charlson index	***	***	***
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.476*	*6.443 (5.237-7.927)*	*<.0001*
≥ 4	*0.9111*	*9.955 (7.138-13.883)*	*<.0001*
Current length of stay >2 days	***	***	***
Admission Sources			
E.D.	*-0.1218*	*0.784 (0.645-0.953)*	*0.0146*
Non-acute Healthcare Facility or Ambulatory	Reference		
Discharge Disposition			
Home	*-0.3111*	*0.647 (0.423-0.989)*	*0.0003*
Assisted Living or Long-term Care	*0.1867*	*1.064 (0.691-1.639)*	*0.0354*
Acute or Sub-acute Rehabilitation Facilities	Reference		
Patient Gender Male	***	***	***

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.13 Imputed General Model for All Patients

	Imputed Model		
	All Patients *(n=36,234)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance			
Medicare	*0.4204*	2.436 (2.074-2.861)	<.0001
Medicaid	-0.0317	1.550 (1.256-1.913)	0.6107
Self-pay	0.0814	1.736 (1.390-2.167)	0.2268
Private	Reference		
Currently Married	*0.0519*	*1.109 (1.014-1.213)*	0.0232
Have a regular physician	*-0.0529*	*0.900 (0.819-0.988)*	0.0272
Charlson index	*-0.0800*	*0.852 (0.774-0.938)*	0.0012
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.1972*	*3.468 (3.123-3.851)*	<.0001
≥ 4	*0.8492*	*6.656 (5.790-7.652)*	<.0001
Current length of stay >2 days	*-0.1717*	*0.709 (0.617-0.816)*	<.0001
Admission Sources			
E.D.	***	***	***
Non-acute Healthcare Facility or Ambulatory	Reference		
Discharge Disposition			
Home	*-0.4075*	*0.521 (0.399-0.681)*	<.0001
Assisted Living or Long-term Care	*0.1631*	*0.922 (0.703-1.210)*	0.0017
Acute or Sub-acute Rehabilitation Facilities	Reference		
Patient Gender Male	*0.0627*	*1.134 (1.032-1.245)*	0.0086

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.14 Imputed General Model for Younger Patients

	Imputed Model		
	18-64 Age Group *(n=16,637)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance			
Medicare	*0.3701*	*2.259 (1.838-2.776)*	*<.0001*
Medicaid	-0.00011	1.560 (1.249-1.948)	0.9986
Self-pay	0.0747	1.681 (1.332-2.122)	0.2779
Private	Reference		
Currently Married	*0.0974*	*1.215 (1.040-1.419)*	*0.0140*
Have a regular physician	*-0.1930*	*0.680 (0588-0.786)*	*<.0001*
Charlson index	*-0.1759*	*0.703 (0.598-0.828)*	*<.0001*
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.1461*	*3.361 (2.813-4.017)*	*0.0221*
≥ 4	*0.9201*	*7.288 (5.896-9.009)*	*<.0001*
Current length of stay >2 days	*-0.1364*	*0.761 (0.618-0.937)*	*0.0102*
Admission Sources			
E.D.	*0.1243*	*1.282 (1.102-1.492)*	*0.0013*
Non-acute Healthcare Facility or Ambulatory	Reference		
Discharge Disposition			
Home	*-0.4924*	*0.538 (0.323-0.894)*	*<.0001*
Assisted Living or Long-term Care	*0.3641*	*1.266 (0.747-2.145)*	*0.0004*
Acute or Sub-acute Rehabilitation Facilities	Reference		
Patient Gender Male	*0.1154*	*1.260 (1.082-1.467)*	*0.0029*

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.15 Imputed General Model for Older Patients

	Imputed Model		
	65+ Age Group *(n=19,597)*		
Variable	Beta Coefficient	Odds Ratio (95% CI)	P value
Insurance			
Medicare	***	***	***
Medicaid	***	***	***
Self-pay	***	***	***
Private	Reference		
Currently Married	***	***	***
Have a regular physician	***	***	***
Charlson index	***	***	***
Admissions in last 1 year			
0 to 1	Reference		
2 to 3	*0.2377*	*3.540 (3.145-3.985)*	*<.0001*
≥ 4	*0.7887*	*6.142 (5.190-7.270)*	*<.0001*
Current length of stay >2 days	*-0.2280*	*0.634 (0.534-0.752)*	*<.0001*
Admission Sources			
E.D.	*-0.1123*	*0.799 (0.722-0.883)*	*<.0001*
Non-acute Healthcare Facility or Ambulatory	Reference		
Discharge Disposition			
Home	*-0.3215*	*0.562 (0.464-0.681)*	*<.0001*
Assisted Living or Long-term Care	0.0670	0.829 (0.690-0.996)	0.0909
Acute or Sub-acute Rehabilitation Facilities	Reference		
Patient Gender Male	*0.0897*	*1.197 (1.079-1.326)*	*0.0006*

*** Indicates Not Significant Variables in the Final Model
Italics Indicates individual factors found significant (p-value < 0.05)

Table 4.16 Final Model Statistical Characteristics

Data Set	**Log-Likelihood**	**C-score**	**HL Goodness of Fit**
General	17628.083	0.705	0.1333
Rural	11141.019	0.6935	0.0648
Urban	5602.103	0.756	<.0001
Expanded Urban	6601.836	0.773	0.0029
Imputed General	14307.868	0.721	0.0494
Imputed Insurance	15934.653	0.712	0.0142
Imputed Married	14575.524	0.718	0.5468
Imputed PCP	14804.768	0.719	0.089
Imputed Charlson	14950.458	0.726	0.297
Imputed Admit	13833.377	0.65	0.0039
Imputed Length of Stay	13673.433	0.716	0.4242
Imputed Insurance & Married	15474.763	0.713	0.2161

4.3 Discussion

From the data received across the hospital sites we were able to develop a set of models using easily obtainable patient level characteristics to modestly predict hospital readmissions. These models were both derived and internally validated for patients admitted to general medicine and ranged over various conditions, insurance statuses, and admission/discharge sources. In addition we generated subset models for specific community hospital settings as well as age groups. An easily identifiable and powerful tool in predicting high risk patients is provided. These models allow for patients classified in particular age groups and hospital sites to be recognized as high risk or not, allowing for hospitals to allocate resources designed to reduce known causes of readmission through intervention processes.

4.3.1 General Model

Interestingly, the all age general model found six factors significant predictors of thirty-day readmission among general in-patients while the other subsequently produced models contained a variation of these predictors. Compared to a similar model produced by Halfon et al. in regards to age classification, however nonclinical, our produced c-statistic was larger at 0.71 than 0.67 [41]. The general model for age group 18-64 did not find that the current length of stay was significant in predicting readmissions and excluded from the final model. While for the same general model the older age group, 65+, found comorbidities as being a non-significant characteristic. These factors were excluded in the final model; as the age characteristic may be further explained by the younger patients' ability to self-regulate and identify clinical deterioration during their longer hospital stay. However not seen in previous models [43, 45, 46, 48], the exclusion of comorbidities in the older group may be explained by both insurance status and admissions within the past year.

For the general and separate age group models, marital status appeared to have a negative correlation with readmission rates, which may be a reflection of more attentive care in identifying and assisting in rising medical signs prior to a required hospitalization. The number of admissions within the last year predicted a significant risk of readmission within 30 days as has been significant and included in other models [28, 41, 47, 49]. Patients admitted 2-3 times in the past year had a three-fold risk of readmission, and patients with more than three prior admissions had a six-fold risk. Another interesting feature in the general model is that for both the aggregated patients and younger age group models Medicare had a positive effect on readmission, while for patients 65 and older it had a negative effect on readmissions. This may be a direct result from the fact that in our hospital sites 97.5% of older patients (65+) are insured under Medicare, allowing age and insurance status to be explained by other compounding factors seen elsewhere in the model (non-significance of comorbidities).

4.3.2 Rural Model

The rural general model observed some characteristics that were previously noted in the general model as all variables were found to be significant for the aggregated all age design. Across the different age schemes however only Charlson Index, admissions in the last year, and current length of stay were repeatedly found as significant. As was identified in the general model the number of admissions within the last year appeared to be the strongest indicator of thirty-day readmission. One particularly interesting discovery was that once again insurance was not an indicator of readmissions for the older age group. For all three rural model's, a current length of stay greater than 2 days had a negative influence on readmissions which does not necessarily align with either the general or urban models.

4.3.3 Urban Model

In the urban general model, similar trends were observed although when it came to classifying high risk patients the number of significant patient factors decreased, three factors (insurance, regular primary care physician, and admissions in the past year) were predictors of the all age urban patient group. These factors however did not all remain the same in the age group models with the removal of insurance status and the addition of length of stay in both collections. In the end, the younger age group found four predictive factors while the older facet found only two to be predictive. The one key patient factor to note is that the number of admissions within the past year provided insight into having a higher correlation to readmission.

4.3.4 Expanded Urban Model

When it came to the expanded urban model, gender was not found to be significant at all while for all groupings the discharge disposition was. Although information regarding where the patient is discharged too, typically is determined later on during the hospital visit it seems to be of added value in identifying those higher risk patients who will not be sent home after their stay. Previously developed models have too observed this relationship [44, 45]. Admission source was only a key patient characteristic when it came to patients 65 and older, with patients arriving from the emergency department having a lower readmission rate than those admitted from a non-acute healthcare facility or ambulatory center.

4.3.5 Imputed Model

The motivation behind the development of this model was to observe the tendencies of a subset of data predicting readmissions and comparing those results to an imputed set where all provided data was utilized. Uniquely enough the all age imputed model had a higher discrimination than the general model with a c-score of 0.721 vs. 0.705, and contained a greater number of variables eight vs. four than the urban expanded model. Although variables are added to this model the significance of admissions in the last year remains strong and appears in all imputed model subsets. Admission source however appears in the separate age group models while excluded from the all patient design as it has an opposing effect on readmissions for the younger and older age groups. In discerning the results seen by the imputation experiment it appears that it strengthens predictability by including all the variables that are available and imputing those missing fields. We currently know that length of stay and admission number may be the most important characteristics and ideally would not want these factors to be missing when prediction readmission probabilities. If insurance or primary care data is not collected upon admission it is not as important as collecting the aforementioned variables and in turn imputing these fields is acceptable, however not ideal. It is better off to impute missing data fields than it is to completely eliminate these specific characteristics.

4.3.6 Model Discussion

The discriminative ability of our models ranged between fair and modest with AUC c-scores of 0.65-0.77 with an overall performance of fair. Compared to similar models observing the same thirty-day readmission as its outcome and utilizing retrospective or real time administrative data, the model with the highest discrimination (largest c-statistic) produced an AUC value of only 0.72 [28]. This model however focused only on congestive heart failure (CHF) patients, and was limited to data from a single United States urban center. Although our models' performance characteristic, in some cases (general & rural), were slightly poorer than some of the previously published it utilized more easily accessible data points than the current models. Creating a model that encompasses community hospital data from both an urban and rural setting had not been provided previously in the literature and combining that along with an age grouping methodology allows one to not diminish the usefulness of these patient factors in predicting/identifying individuals at high risk. Overall the number of admissions within the past year for any patient across the various models and different age groups tends to be the strongest indicator for a readmission and a major factor in identifying high risk patients. With this being the case, clinicians should be aware of how often and how many times a particular patient has been previously admitted in order to properly tailor discharge interventions [17-20] aimed at reducing readmissions. Current practice calls for various intervention bundles targeted at post-discharge support [21], front-loaded home care [22], remote monitoring [23], and self-management [24]. As soon as a particular patient has been identified as high risk a particular intervention or set of intervention steps should be conducted in order to assist the patient in reducing their chance of being hospitalized once again. With the models put forth, both nurses and physicians can adjust discharge protocols for a particular patient instead of classifying patients based on condition or age and assigning them an intervention. It appears to be beneficial to operationalize a set of interventions for different high risk patient groups to ensure that each discharged patient receives proper care centered on their particular risk factors (e.g., follow-up appointment with patient’s primary care provider within 5-7 days of discharge, patient and spouse group medication education for older patients).

In summary, a few prediction models have been developed to successfully identified patients at elevated risk of hospital readmission within 30 days of discharge, in a community based multi-center cohort of general medicine inpatients. Although the patient population is diverse, additional work is needed to identify external factors that impact post-discharge health outcomes, optimize the discharge process for patient groups, and create patient specific interventions to prevent avoidable readmissions. The next step for this work is to develop a decision support tool which takes these models and provides clinicians and hospital administrators a means to use these results in a hospital setting.

Table 4.17 Conclusion Summary for Individual Model Design

Model Design	**Conclusion**
General	• Significant patient characteristics in predicting readmissions for all patients; insurance status, marital status, having a primary care physician, Charlson Comorbidity Index, admissions within the last year, and length of stay • The model for age group 18-64 did not find current length of stay was significant, while the older age group, 65+, found comorbidities as being a non-significant characteristic
Rural	• All variables found in the general all age model were significant in the rural all age design • Across the different age schemes only Charlson Index, admissions in the last year, and current length of stay were repeatedly found as significant
Urban	• Three factors (insurance, regular primary care physician, and admissions in the past year) were predictors of the all age urban patient group • The number of admissions within the past year provided insight into having a strong readmission predictability
Expanded Urban	• Gender was not found to be significant at all while for all age groupings the discharge disposition was a predictor • Discharge disposition information is of added value when predicting readmissions
Imputed	• All age imputed model had a higher discrimination than the general model with a c-score of 0.721 vs. 0.705 • Contained a greater number of variables eight vs. four than the urban expanded model • The significance of admissions in the last year remains strong and appears in all imputed model subsets

CHAPTER 5. DECISION SUPPORT

5.1 Methodology

We set out to develop a readmission simulator, in collaboration with Purdue Healthcare Advisors and funded by the Indiana Hospital Association through the Partnerships for Patient Initiative, in order to expand upon the general model research results found in Chapter 4. The motivation behind this tool was to give ‘control’ back to hospital administrators to improve the decision making process. As a result this decision support model was designed for hospitals to; estimate the risk of readmission for a patient population, choose the most appropriate set of interventions for a given population, estimate cost/benefits of implementation, and perform ‘what if?’ analyses. It allows hospitals to easily apply readmission risk models to discharged patients and estimate the impact of multiple intervention scenarios on their readmission risk profile and revenue stream. Thus, users of this software can estimate the benefits and associated costs of intervention selections in a predictive manner without real world experimentation. This model allows hospitals to extract hospital specific data from electronic medical records (EMR) and run different forms of predictive analytics on thirty-day readmissions, descriptive statistics, and compare results from intervention implementation.

5.2 Software Design

The decision support package consists of two components: the *Readmissions Data Template* and the *Readmissions Simulator*. The first is an Excel file into which hospital discharge data is loaded and processed. The second is an AnyLogic® Java based simulator that reads the data, presents descriptive statistics, and allows the user to perform 'what if' analyses. These analyses estimate the impact of patient population characteristics and readmission reduction methods on thirty-day readmission risk, expected prevented thirty-day readmissions, and hospital revenues. There are a few reasons that these two programs were selected as the interactive interfaces. Many individuals are now well versed in using the capabilities provided in Microsoft Excel and can easily compile patient discharge data into appropriate locations, given certain specifications. In addition, AnyLogic® is a user-friendly platform where end-users may be able to manipulate different intervention, payment adjustment, and 'high-risk' patient threshold scenarios through simple radio buttons and sliders. This software simplifies the experimentation process for simulating discharge interventions by displaying options and results in a clear straightforward manner. To supplement the software package a user guide was developed which lays out the foundation for the products use as well as step by step instructions to walk the user through both tools.

5.3 System Requirements

As with any program there are certain system requirements as detailed below:

1. Microsoft Windows 7 or later, Vista, Apple Mac OS X 10.6 or later
2. Excel 2007 or newer with macros enabled

3. Java 2 Standard Edition 6.0 or later JRE 1.6.0 or later (if not using Windows)

5.4 Readmission Data Template

This part of the decision support tool is where the user is required to place specific patient discharge data as specified. The data types that are required by the user includes; Unique ID, Payer Type, Marital Status, Primary Care Physician, DRG & ICD-9 codes, Date of Admit & Discharge, and Patient Age (Figure 5.1). These fields are to be properly filled out for each discharge as these characteristics were revealed to be the significant factors in predicting a patient's readmission probability. Users will notice that the final column, *Number of Admits in Last Year*, is colored differently in order to remind users that this is not a required field to be imported into the template as it is internally computed. This was not required because EMR systems vary in capabilities and may or may not have had the ability to computing this factor. Therefore, we determined standardization of this value would be ideal and calculate it internally. Leaving this column blank can be used as a mechanism to ensure that all calculations were done properly, as this will only be filled out once that is accomplished.

1	Unique ID	Payor Type	Marital Status	PCP	DRG	Dx .1 (Primary)	Dx .2	Date of admit	Date of discharge	Age
2	10006	O-MEDICARE	DIVORCED	Last, First	191	491.22	518.83	28-Jun-12	02-Jul-12	65
3	10133	PCCM - MEDICAID	M	NONE,DOCTOR	378	578.9	285.1	1/3/2012	Thursday, May 10, 2012	67
4	10192	Self Pay	SINGLE		394	569.49		1/5/2013	02-Jul-13	70

Figure 5.1 Example of Readmission Data Template with Discharge Data
Note: Dx.3- Dx.10 eliminated for this example only

This template computes a few additional characteristics across the uploaded data set to be observed in the *Readmission Simulator* as descriptive statistics. This will be discussed later in more detail in Section 5.5. Another feature of this file is that it filters and organizes discharge data by unique id, grouping discharges by patient with the most recent admission first. This data organization allows administrators and end users to visually observe trends among a particular patient with multiple hospitalizations. In addition, all patients under the age of 18 are disregarded for readmission computations as these individuals are not subject to hospital penalization. All data manipulation and calculations are controlled by a macro named *Readmission Calculation* with the code for this program to run written in Excel VBA. Once all fields are adequately filled out and the designed ActiveX macro button *Readmission Calculation* is selected and ran a secondary Excel file is created. This file named *DataSet* contains the necessary information to be read in by the simulator including the descriptive statistics and individual discharge readmission probabilities.

5.5 Readmission Simulation: Population Prediction

Upon opening the simulator, the *DataSet* file is read in to properly display the appropriate statistics and computed readmission data. This occurs while the user views the *Main Menu* screen which introduces the user to the prediction tool and allows for either individual prediction or population prediction to be selected (Figure 5.2). For now we will discuss the *Population Prediction* option.

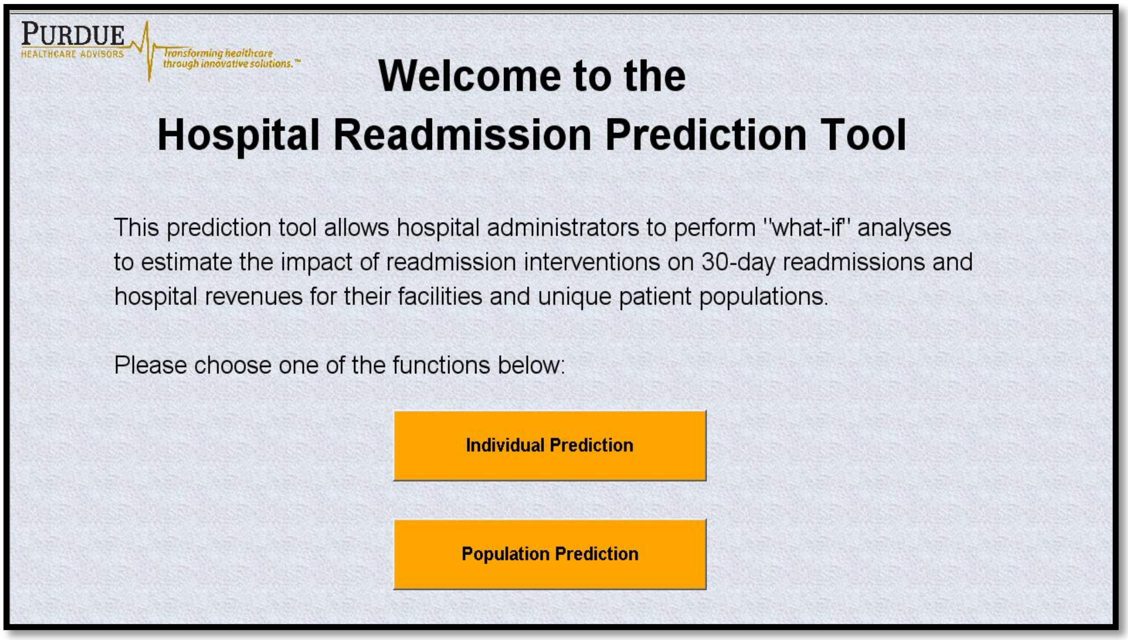

Figure 5.2 Readmission Simulator Main Menu

Once this choice is selected, a second screen appears (Figure 5.3) where users can adjust the readmission payment adjustment factor, view descriptive statistics, select interventions and regulate ‘high-risk’ threshold, simulate the selected interventions, and observe readmission probability distributions. To supplement the simulated interventions number of expected readmissions avoided and hospital adjusted revenue are provided for decision support to identify the proper intervention/threshold mixture. The provided readmission payment adjustment factor ranges from 0.97-1.0 in order to mimic where the maximum penalty (3%) will be for FY 2015. A factor of 1 indicates that no penalty is applied, while a factor of 0.97 indicates that the hospital revenue will be penalized 3% of all Medicare revenue.

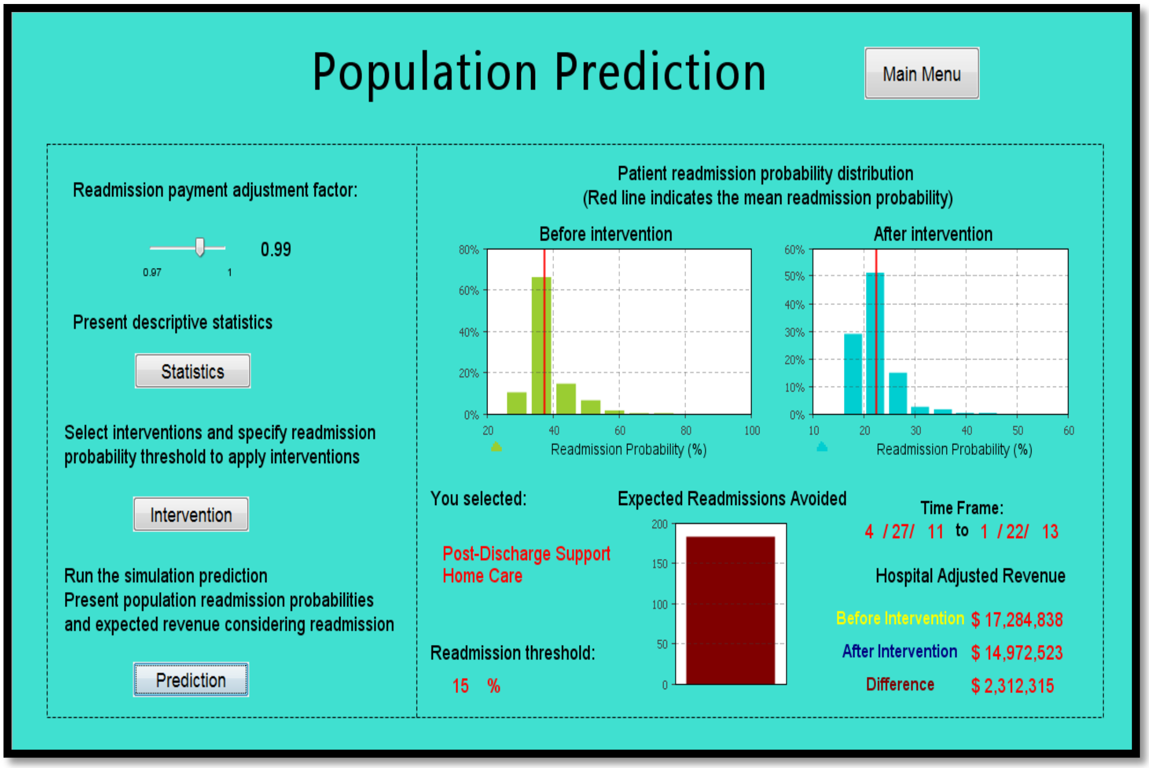

Figure 5.3 Population Prediction User Interface

Clicking the *Statistics* button allows the user to display descriptive statistics based on the loaded data, which is shown in (Figure 5.4). The descriptive statistics present the earliest and latest discharge dates in the data file as well as the total numbers of discharges, unique patients, thirty-day readmissions, and unique readmitted patients. This includes pie charts showing the number of discharges and thirty-day readmissions by; patient age, insurance type, marital status, availability of regular primary care physician, and comorbidity level.

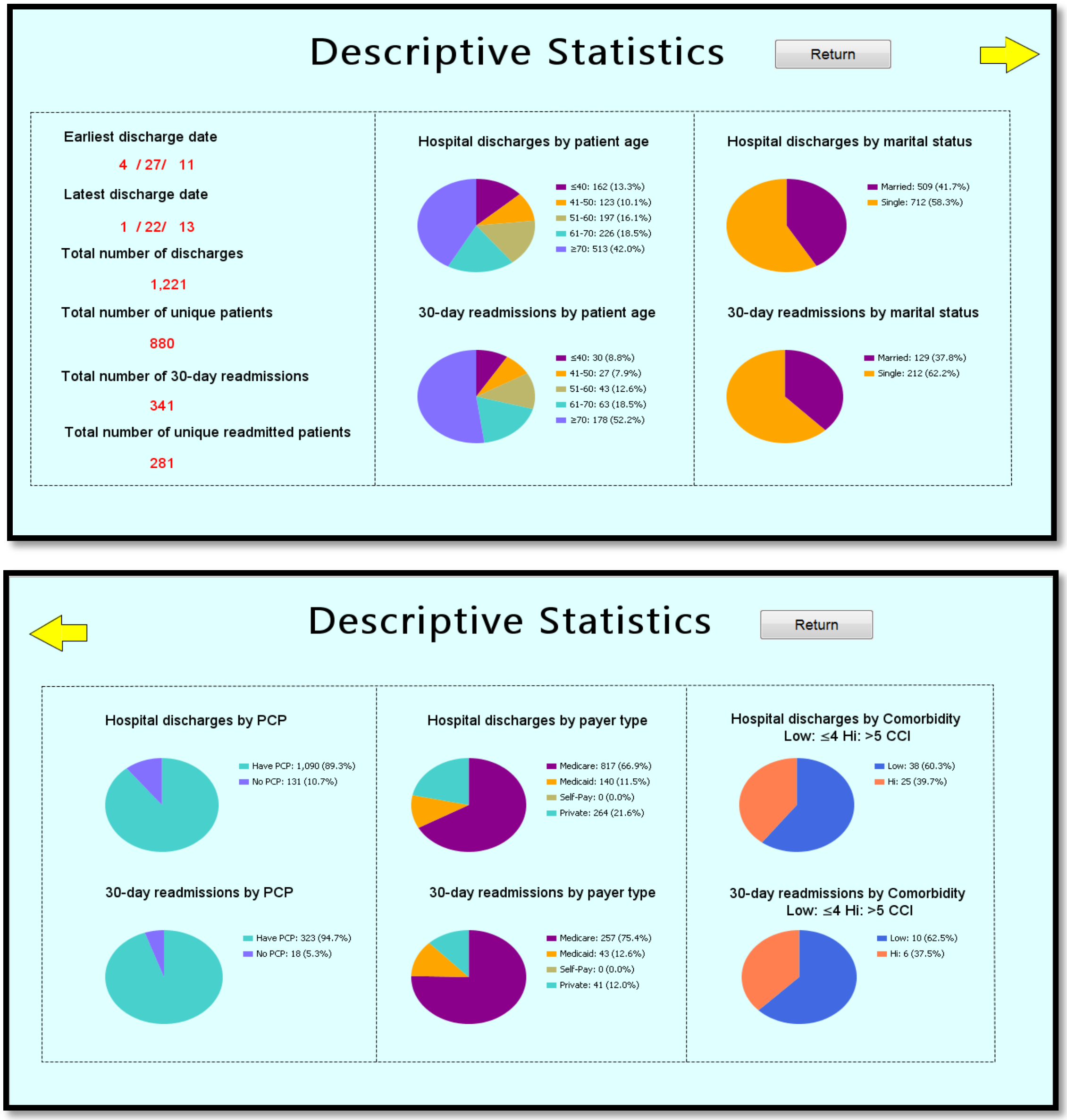

Figure 5.4 Descriptive Statistics for the Hospital Discharge Set

In returning back to the *Population Prediction* screen the user has the option of selecting any combination of interventions and readmission threshold by clicking the *Intervention* button. In the interventions interface, the user can select the desired interventions to reduce the patient's readmission probability (Figure 5.5). There are five intervention options that can be selected as were identified in the literature review (Sections 2.8 through 2.12) to be the 'golden standards' encompassing the various intervention programs. These interventions are Project RED [18], post-discharge support [21], front-loaded home care [22], remote monitoring [23], and self-management [24]. Multiple interventions can be selected to be jointly simulated over the entirety of the hospital discharge set given the chosen probability threshold. In order to adjust for the interaction of multiple interventions an established mathematical mechanism was used as described in (Eq. 5.1-5.4). For each patient with readmission probability greater than the selected threshold:

$$P_i{}' = P_i \prod_{i=1}^{|\gamma|} (1-\gamma_i)^{\frac{1}{i}} \qquad (5.1)$$

$$\gamma = < \gamma_{(i)} | \, I_i = 1 > \qquad (5.2)$$

$$\gamma_{(1)} = Max \, < \gamma_{(i)} | \, I_i = 1 > \qquad (5.3)$$

$$\gamma_{|\gamma|} = Min \, < \gamma_{(i)} | \, I_i = 1 > \qquad (5.4)$$

$P_i{}' - readmission\ probability\ after\ intervention\ applied$

$P_i - readmission\ probability\ before\ intervention\ applied$

$n - number\ of\ interventions\ selected$

$I_i - intervention\ selected\ i = 1\ to\ N$

$\gamma_i - readmission\ reduction\ rate\ for\ intervention$

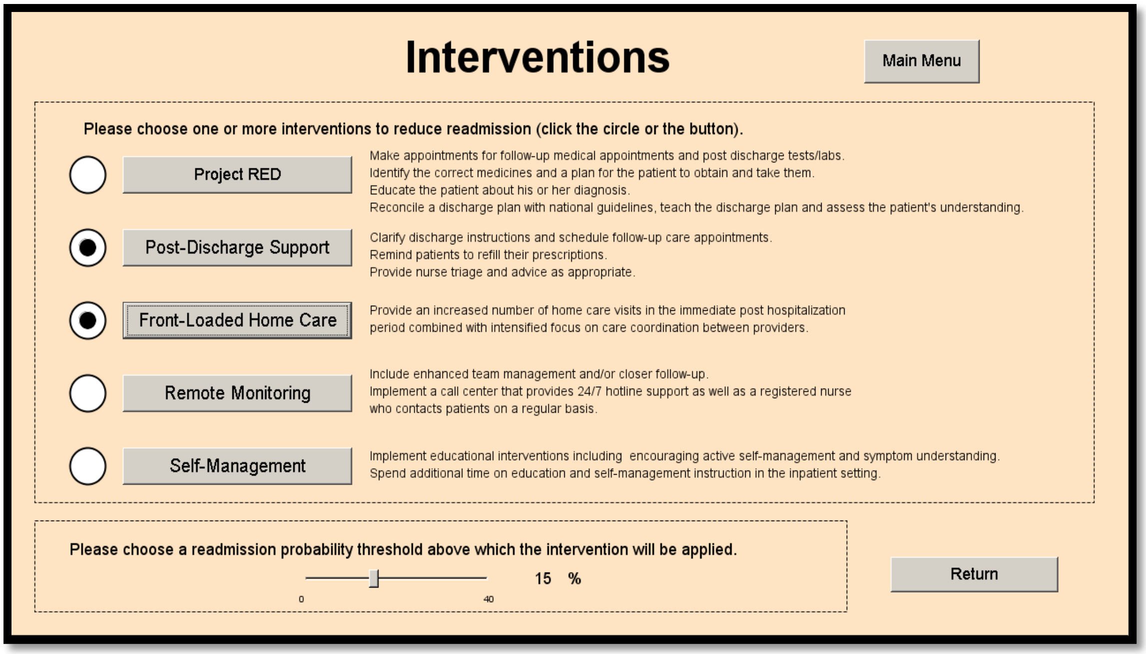

Figure 5.5 Intervention Selection Menu

After selecting the intervention(s), users can click the *Prediction* button which will allow the user to observe the prediction readmission probabilities. The top two charts shown in Figure 5.6 are a histogram of predicted readmission probabilities before implementing interventions (left) and after implementing interventions (right). The bottom bar chart shows the expected readmissions that would be avoided after implementing the selected interventions. The expected number of readmissions avoided is computed in the manner shown in Eq. 5.5.

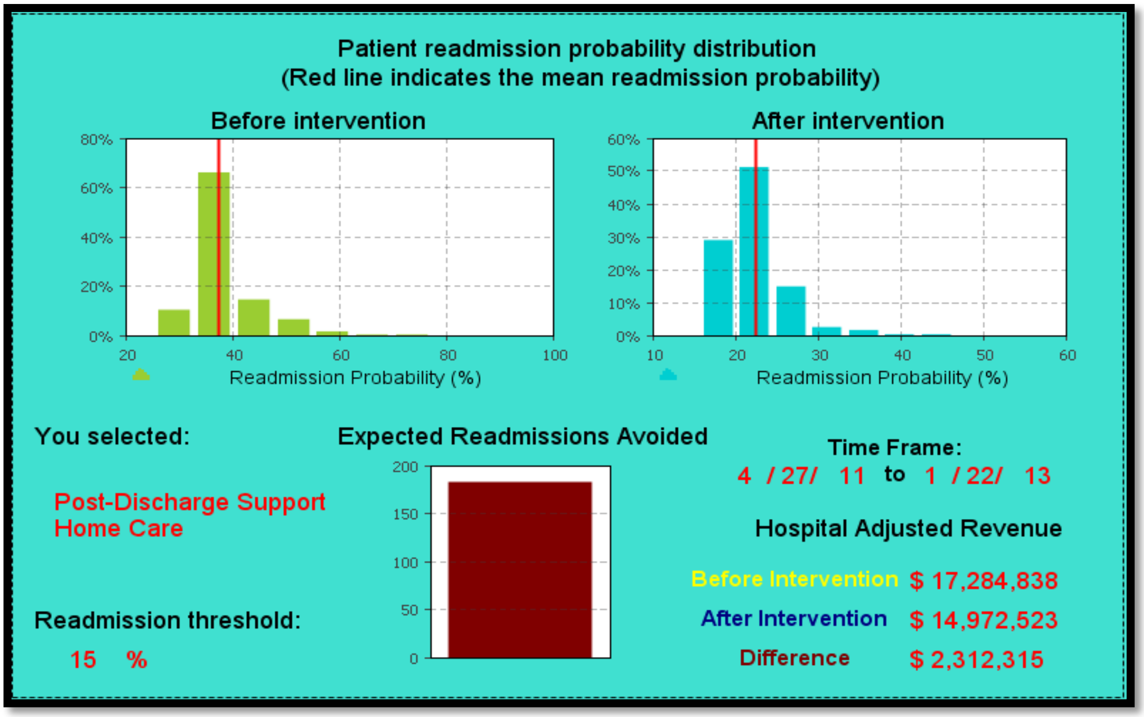

Figure 5.6 Patient Readmission Probability Distribution Histograms

$$R = \sum_{i=1}^{M}(P_i' - P_i) \qquad (5.5)$$

$R - number\ of\ expected\ readmissions\ avoided$

$M - total\ number\ of\ patients$

Next to this graph, users will find the *Hospital Adjusted Revenue*, with before and after intervention estimates along with the subsequent difference between the two. For health administrators to make the best possible decision for their facility they need to possess all the facts. Therefore the development of a financial model simulating a revenue stream is essential to proper decision making. The decision support tool performs a revenue and cost analysis to provide end users with this capability once desired interventions are implemented. In order to create a feasible structure certain assumptions are required. This model captures discharges as either Medicare or a non-Medicare with an associated average cost per patient, as provided by CMS [91, 92].

Subsequently, the *Medicare Readmission Payment Adjustment Factor* is applied to all Medicare revenue [11, 13]. Prevented readmissions are not considered in the revenue stream after interventions are applied. In addition, the costs of selected interventions, for qualified patients are deducted from the revenue. Several factors could not be quantified and therefore were not included in the final financial model. Revenue generated from increased out-patient revenue to the hospital/network (PCP, lab work, etc.) and revenue from other patients (increased capacity from beds available due to non-readmitted patients) was excluded from calculations. In addition, the increased capacities of staff or labor cost reductions were omitted. Any improved quality scores and all financial incentives were not considered, as correlated to a higher reimbursement rate from third-party payers. All used cost parameters and revenue estimates are shown in Table 5.1. Overall, the presented model found in the support tool is rudimentary covering the basics of the healthcare payer structure. This financial model, at the current state, provides an adequate insight for informative decision making while exposing the interactions of readmission rates, interventions, and the penalties incurred by hospitals.

Table 5.1 Simulator Revenue and Cost Estimates

Cost Parameter	*Value ($)/pt.*	*Reference*
Revenue per Medicare discharge	10,737	[91]
Revenue per non-Medicare discharge	10,006	[92]
Project RED	122	[93]
Post-Discharge Support	116	[21]
Front-Loaded Home Care	228	[22]
Remote Monitoring	424	[25]
Self-Management	100	[24][18]

5.6 Readmission Simulation: Individual Prediction

In order to maximize the usefulness of this tool for monitoring patients during their admission, an individual patient prediction option was developed. This support option utilizes the same general model characteristics and methods established in Chapter 4 and seen in the *Population Prediction* section. By observing the success of an electronic version of the LACE tool, which identified patients at high risk, added motivation as we developed our own version in the *Individual Prediction* interface [57, 94, 95]. After clicking the *Individual Prediction* button in the *Main Menu*, users will see the interface shown in Figure 5.7.

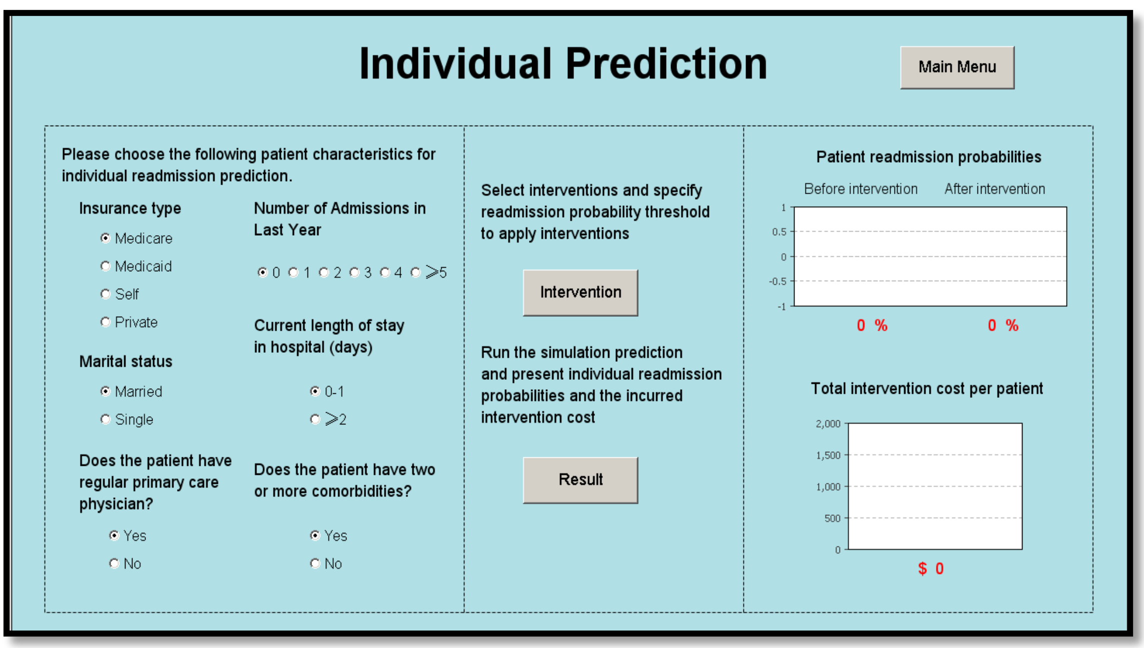

Figure 5.7 Individual Prediction User Interface

The left section of the user interface contains several radio buttons from which users can specify the characteristics of the given patient. These characteristics were the ones found to be significant in our prior study and include insurance type, marital status, admissions in the past year, current length of stay, comorbidity, and availability of regular primary care physician. For the case of comorbidities, this can be defined as two or more medical conditions presented simultaneously within a patient at the time of the current admission. In a manner similar to the population prediction, users can select desired interventions and respective ‘high-risk’ threshold. After selecting the intervention(s), users can click on the *Result* button to see the predicted readmission probabilities before and after applying the selected intervention(s). In Figure 5.8 the bar chart on the top right shows two bars which are the readmission probabilities before intervention(s) (left) and after intervention(s) (right). The bar chart at the bottom shows the total estimated cost for the selected intervention(s).

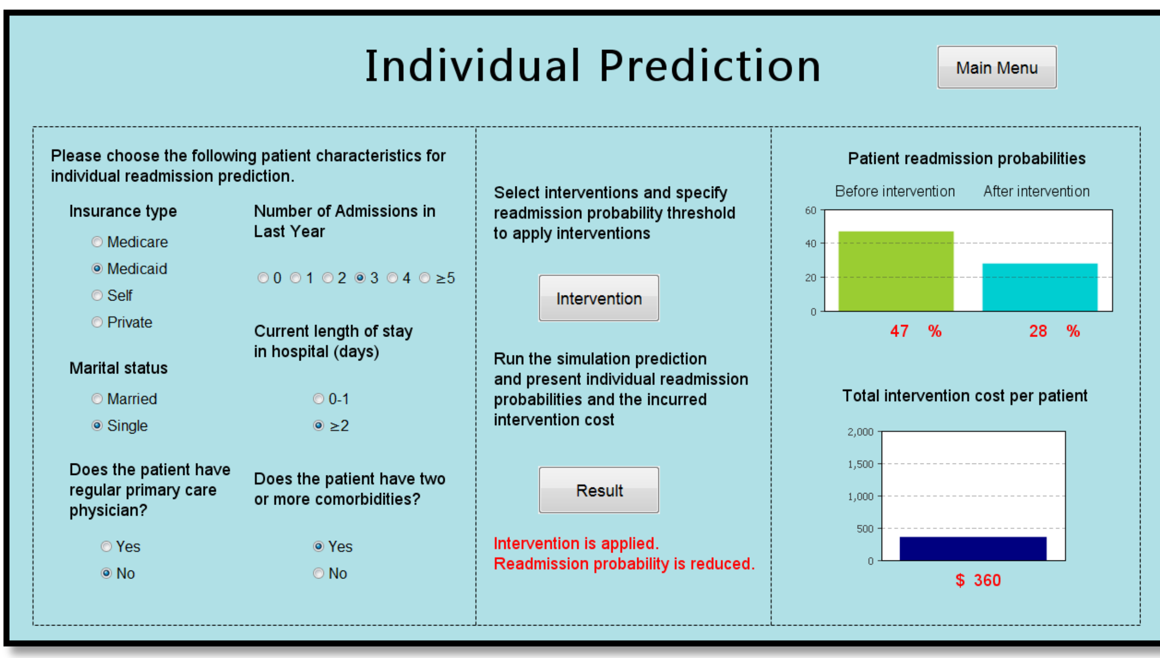

Figure 5.8 Individual Prediction Interface with Readmission and Intervention Calculation

CHAPTER 6. CONCLUSIONS

By combining the results found in Chapter 4 with published discharge intervention work we were able to produce an interactive decision support tool (Chapter 5) which gave informative power to healthcare administrators. In addition, this work was unique in developing five innovative readmission prediction models in the area of general medicine in-patients admitted to community hospitals, through an aggregated and age group classification approach. Being able to generate general aggregated models provided an overall view of the significant patient characteristics in predicting readmissions for all patients; insurance status, marital status, having a primary care physician, Charlson Comorbidity Index, number of admissions within the last year, and current length of stay (>2 days). Furthermore, the investigation of these models by community hospital site (rural vs. urban) demonstrates the importance of specialized predictive models based on location. Creating a more focused model by hospital setting and patient age provides a more targeted readmission estimate and strengthens predictability. We were able to discover the importance of establishing models based on full data sets as opposed to throwing out critical variables and discharges if not available. It was found to be more acceptable to impute these missing characteristics than to fully discard them from all analysis.

This foundation provides insight to clinicians allowing them to target ‘high-risk’ patients with identified intervention strategies. Previously established research in the area of discharge interventions surround four major areas; post-discharge support [21], front-loaded home care [22], remote monitoring [23], self-management [24]. Along with the widely found success these interventions have been bundled in several packages as proven to wholly reduce readmission probabilities. However, operationalized process work flows that identify the impact of individualized bundle steps have yet to be developed. In response, we developed standardized step-by-step process flows with identified resources for a set of three acknowledged interventions; comprehensive discharge planning, medication self-management, and disease self-management.

The decision support tool helps out health administrators by allowing them to observe their historic in-patient populations’ readmission probability distributions. This is further strengthened by providing users with the tools to simulate changes in revenue streams, readmission probabilities, and number of avoided readmissions if certain discharge interventions where put into place. This is a much easier process to test quality improvement metrics than to clean house each time administrators want to test a new intervention process. In addition, clinicians and decision makers are provided a set of descriptive statistics that gives them a look into their own hospitals to quickly identify characteristics of all patient populations versus readmitted patients. With this type of knowledge individuals can look at visual charts and begin identifying areas where readmission work would be the most beneficial and provide the greatest improvements. The support tool also points out whether or not the ‘readmitted’ patients are the same ones each time, resulting in isolated instances, or is it truly an issue across the board.

6.1 Limitation

Our mathematical readmission prediction study has several limitations. Though it was conducted at multiple (three) community hospitals, both rural and urban, across Indiana and included a sizeable and diverse patient population, caution should be applied in generalizing its findings to academic, small, critical access, and/or hospitals in other states nationwide. We excluded patients who died within 30 days of discharge because predictors of death may be different than predictors of readmission thus skewing our analysis. We were not able to differentiate between an elective versus unplanned readmission, and therefore we could not exclude planned readmissions. Lastly, we were not able to track any hospitalization and/or readmission to non-study hospitals either within Indiana or outside.

6.2 Areas of Future Research

Given these limitations there are multiple avenues to consider for future research. We can conduct this study with a larger hospital sample size in rural and urban community settings in multiple states across the United States. This would allow us to determine if the readmission factors differ based on patient geographical location or if similar traits are observed nationwide. In addition, this would strengthen both urban and rural models while assessing the importance of age categorization. We may consider additional variables both administrative and self-reported data in the realm of socio-economic status, mental status, and hospital quality ratings.

With the charted work flows we can begin partnering up with multiple community hospitals to test the impacts financially and on readmission rates for the three prominent discharge intervention processes. In order to properly asses the intervention impacts they must be tested at multiple hospital sites with similar attributes (size, location, etc.). In addition, these interventions must be tested when coupled together or when all three are implemented at the same location. Conducting such work will either provide justification for the 'bundled' intervention approach, seen in Project RED and BOOST to name a few, or indicate a single intervention to be the most effective financially and in reducing readmissions. This should be done in a random fashion in order to observe effects on patients admitted to the same hospital while attempting to eliminate researcher/clinician bias.

In regards to the decision support tool there are several areas where future work can be contributed. By utilizing the research and findings of different models for urban and rural settings the tool should allow users to indicate location. Providing this option would better tailor readmission prediction probabilities instead of using the general model findings. Currently the organization that created an official system of assigning the coding structure for procedures and diseases, International Statistical Classification of Disease (ICD) and Related Health Problems, is changing from the ninth to the tenth revision (ICD-9 to ICD-10) [96]. In turn the current version of the software only accounts for ICD-9 and will not be able to handle and run computations for the revised coding version. As a result we much provide an option to users in order to determine which coding type was used for the readmission prediction. Lastly, to best ensure real-time patient prediction and identifying ideal interventions for a targeted individual we should integrate the foundation of this tool into electronic medical records. While the shift for all hospitals nationwide trends to EMRs, being able to intertwining this predictive modeling would improve user responsiveness to this ‘high-risk’ identification as all would be contained in a centralized program.

We are confident in the work that was done in the area of predicting patients at high-risk of thirty-day readmission contributes to healthcare operations research. In addition, operationalizing significant discharge intervention work flows allow clinicians in the future to identify a standardized process aimed at reducing readmissions. Consequently, these collaborative efforts in mathematical design, intervention process improvement, and financial modeling produced an interactive user friendly decision support tool. Together predicting and reducing readmission rates can be achieved in a cost effective manner with all options considered.

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